Algorithm Theoretical Basis Document (ATBD) for the Conical-Scanning Microwave Imager/Sounder (CMIS) Environmental Data Records (EDRs)

Volume 9: Soil Moisture EDR

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RELATED CMIS DOCUMENTATION

Government Documents

Title	Version	Authorship	Date
CMIS SRD for NPOESS Spacecraft and Sensors	3.0	Associate Directorate for Acquisition NPOESS IPO	2 March 2001

Boeing Satellite Systems Documents

Title		Covering
ATBD for the CMIS TDR/SDR Algorithms		
ATBD for the CMIS EDRs	Volume 1: Overview	Part 1: Integration
		Part 2: Spatial Data Processing • Footprint Matching and Interpolation • Gridding • Imagery EDR
	Volume 2: Core Physical Inversion Module	
	Volume 3: Water Vapor EDRs	Atmospheric Vertical Moisture Profile EDR Precipitable Water EDR
	Volume 4: Atmospheric Vertical Temperature Profile EDR	
	Volume 5: Precipitation Type and Rate EDR	
	Volume 6: Pressure Profile EDR	
	Volume 7: Cloud EDRs	Part 1: Cloud Ice Water Path EDR
		Part 2: Cloud Liquid Water EDR
		Part 3: Cloud Base Height EDR
	Volume 8: Total Water Content EDR	
	Volume 9: Soil Moisture EDR	
	Volume 10: Snow Cover/Depth EDR	
	Volume 11: Vegetation/Surface Type EDR	
	Volume 12: Ice EDRs	Sea Ice Age and Sea Ice Edge Motion EDR Fresh Water Ice EDR
	Volume 13: Surface Temperature EDRs	Land Surface Temperature EDR Ice Surface Temperature EDR

Title		Covering
	Volume 14: Ocean EDR Algorithm Suite	Sea Surface Temperature EDR Sea Surface Wind Speed/Direction EDR Surface Wind Stress EDR
	Volume 15: Test and Validation	All EDRs

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1. Abstract

The CMIS Soil Moisture EDR will be retrieved by a robust algorithm that adapts to changing surface water and vegetation cover conditions. Open water fraction is derived by a empirical-statistical approach from CMIS observations at the 20 km scale (18 GHz and up).and averaged up to the 40 km soil moisture retrieval cell. After adjusting for open water (if present), a physical-statistical retrieval algorithm derives soil moisture for the remainder of the cell from 40 km CMIS observations (6 and 10 GHz). By-products of the physical retrieval include vegetation water content (a measure of vegetation density) and diagnostic parameters indicating goodness-of-fit of the solution to measurements. In nominal algorithm operations, algorithm inputs include emissivities and LST derived by the atmospheric algorithm core module. However, multiple alternative modes allow for top-of-atmosphere brightness temperature inputs or reduced channel or LST availability. In this ATBD we describe the physical basis and mathematical structure of the algorithm, its inputs, its implementation and data flow within the CMIS processing concept, and its expected performance based on extensive testbed simulations. Performance is expected to meet or exceed EDR requirements. Future algorithm calibration, testing, and operational considerations are discussed. We also present real-data algorithm trials conducted with the TRMM (Tropical Rainfall Measuring Mission) Microwave Imager (TMI) and the Scanning Multichannel Microwave Radiometer (SMMR) that demonstrate robust and consistent EDR production and algorithm flexibility.

2. Introduction

2.1. Purpose

The purpose of this document is to provided all the information necessary to understand, operate, further develop, and use the products from the CMIS Soil Moisture EDR retrieval algorithm. The CMIS SRD (NPOESS IPO, 2000) specifies the soil moisture EDR's required (threshold level) operational and performance characteristics including definitions, spatial resolution, and measurement range and uncertainty. The algorithm is designed to meet these specific requirements by deriving soil moisture from CMIS brightness temperature observations. Furthermore, the algorithm reports additional products that extend the retrieval capabilities and aid quality control.

Section 3 summarizes the EDR requirements either specified in the SRD or derived from it. It contains a historical background and physical basis for the proposed algorithm, and it describes the instrument characteristics and data from all sources necessary to meet NPOESS requirements.

Section 4 describes the physical parameterizations relevant to the soil moisture retrieval algorithm. We also provide algorithm processing flow diagrams including dependencies within the overall processing flow and list input and output fields.

Section 5 presents both simulations and real-data test results and provides measurement uncertainty and other performance estimates based on the tests. These estimates are used to demonstrate that the algorithm products will satisfy retrieval performance requirements. We describe the environmental conditions under which we expect the retrieval to meet requirements, not to meet requirements, or to degrade substantially. We also summarize special constraints, limitations, or assumptions made in algorithm parameterization or testing that may limit the algorithm's applicable domain or necessitate post-launch adjustments based on specific systematic contributions in order to meet performance estimates.

Section 6 discusses algorithm calibration points and outlines the steps necessary to transition algorithm operation from simulated-data to a CMIS-data inputs. We outline considerations for pre- and post-launch calibration and validation efforts, including needed measurement capabilities and hardware, field measurements, and existing sources of truth data.

Section 7 describes practical considerations including numerical computation considerations, algorithm quality control and diagnostics, exception and error handling, and archival requirements.

2.2. Document Scope

The *ATBD for the CMIS Soil Moisture EDR* covers algorithm operations beginning with the ingestion of earth-gridded Core Module products (surface effective all-band microwave emitting temperature and broad-band atmospheric window-channel emissivities) and/or brightness temperatures and concluding with the reporting of the Soil Moisture EDR and other related algorithm products on the same earth grid. Preceding sensor data processing steps are covered in the *ATBD for SDR Processing* and *ATBD for the Core Physical Inversion Module* (AER, 2000). This ATBD provides outlines for continued algorithm development and advancement and for pre- and post-launch calibration/validation efforts. These outlines are intended to be reviewed and revised prior to launch as new data sources and research become available.

3. Overview and Background Information

3.1. Objectives of the Soil Moisture EDR retrieval

The Soil Moisture EDR is a specific measurement that CMIS must perform to complete the mission objectives stated in the SRD: "The mission of CMIS is to provide an enduring capability for providing measurements on a global basis of various atmospheric, land, and sea parameters of the Earth using microwave remote sensing techniques. The CMIS instrument will collect relevant information from a spaceborne platform, and utilize scientific algorithms to process that information on the ground into designated [EDRs]." (SRD, section 3.1.7)

The SRD requires that, at a minimum, the algorithm must retrieve surface layer (0.1 cm) soil moisture for bare (exposed) soil as well as vegetated terrain. The CMIS soil moisture retrieval will provide an instantaneous estimate of soil moisture in the top (0-0.2 cm) layer of the soil averaged over 40 km cells in clear and cloudy (non-precipitating) conditions. At this spatial resolution, the product is more able to resolve atmospheric-scale processes (antecedent precipitation and drying) than surface-scale effects on soil moisture (soil type, topography, surface cover). As such, the product may be most valuable as a measure of atmospheric processes and land-atmosphere feedbacks or as a regional basis for a down-scaling algorithm using higher-resolution measurements. The algorithm will also provide surface water measurements (described next) in clear and cloudy conditions which should be valuable for monitoring large-area flood events.

To accommodate the possible presence of surface water, the algorithm will estimate three surface moisture products: The EDR's cell-average surface moisture including open water (as per the EDR definition), fractional coverage of open water, and soil moisture in the cell's non-water covered surfaces. These products may provide useful flood monitoring capabilities in the absence of precipitating cloud cover.

To accommodate vegetation cover, the algorithm will estimate the retrieval cell's average vegetation water content (or VWC, defined as mass of water in vegetation per unit area). This retrieval is performed simultaneously with the retrieval of soil moisture in the non-water covered fraction of the cell. The proportion of global lands that are either bare (about 10% excluding ice caps) or sparsely vegetated (about 25%) allows the useful application of the algorithm to about 35% of non-ice-covered lands. (Percentages are based on 50 km aggregation of the USGS 1 km *Global Land Cover Characterization* dataset.) Alternative approaches that may provide more useful real-time soil moisture estimates for heavily vegetated terrain include atmospheric-hydrologic modeling or lower frequency (1.4 GHz) measurements. Aside from quality control issues, this ATBD does not further cover soil moisture estimation methods for heavily vegetated terrain.

Accurate soil moisture retrieval may be achieved over a broader range of vegetation conditions if both 10 and 6 GHz CMIS channels are available to the algorithm. Inclusion of 6 GHz data—which has lower spatial resolution (50 km when enhanced) than 10 GHz but generally superior soil moisture and vegetation cover measurement capabilities—requires increased attention to errors induced by spatial heterogeneity and anthropogenic microwave noise sources. (See section 5.) Nevertheless, our flexible algorithm design allows a variety of input data types and combinations to produce robust retrievals even where contaminated inputs are detected.

The CMIS soil moisture products will complement the soil moisture EDR required for the VIIRS instrument. Whereas CMIS can make an instantaneous measurement in clear and cloudy conditions at 40 km scale, the VIIRS instrument requires clear skies—and, if a thermal inertia-type algorithm is used, a day-night observation pair—to make 1 km-scale soil moisture estimates. Furthermore, the VIIRS retrieval may require ancillary inputs to calibrate the retrieval and some of these may be provided by CMIS.

3.2. Summary of EDR requirements

3.2.1. SRD Requirements

The text below and Table 3-1 are the portions of CMIS SRD section 3.2.1.1.1.1 that apply directly to the soil moisture algorithm. Shading indicates attributes not addressed at all in this document.

Soil Moisture **TRD App D Section 40.2.6**

Total liquid water in the soil or in a surface layer over soil. The threshold requirement is to measure soil moisture within a thin layer at the surface (0.1 cm) for bare soil in regions with known soil types, as well as, soil moisture for vegetated terrain. The objective is to measure a moisture profile for any soil, whether bare or not, and whether or not the soil type is known.

Table 3-1: SRD Requirements for the Soil Moisture EDR

Para. No.		Thresholds	Objectives
C40.2.6-1	a. Horizontal Cell Size	40 km	1 km
C40.2.6-2	deleted		
C40.2.6-3	b. Horizontal Reporting Interval	(TBD)	(TBD)
C40.2.6-4	c. Vertical Cell Size	Skin layer	5 cm
C40.2.6-5	d. Vertical Reporting Interval	N/A (single value reported)	5 cm
C40.2.6-6	e. Horizontal Coverage	Land	Land
C40.2.6-7	f. Vertical Coverage	Skin layer	0 to –80 cm
C40.2.6-8	g. Measurement Range (volumetric)	0 – 100%	0 – 100%
C40.2.6-9	h. Measurement Uncertainty (volumetric)	10% (TBR)	5%
C40.2.6-10	deleted		
C40.2.6-11	i. Mapping Uncertainty	3 km	1 km

Para. No.		Thresholds	Objectives
C40.2.6-12	j. Swath Width	1700 km	3000 (TBR)

In addition to these requirements, the SRD specifies:
1. "Science algorithms shall process CMIS data, and other data as required, to provide the [EDRs] assigned to CMIS." (SRD, paragraph SRDC3.1.4.2-1)
2. "Specified EDR performance shall be obtained for any of the orbits described in paragraph 3.1.6.3 …" (SRDC3.1.6.3-2)
3. "As a minimum, the EDR requirements shall be satisfied at the threshold level." (SRDC3.2.1.1.1-3)
4. "… the contractor shall identify the requirements which are not fully satisfied, and specify the conditions when they will not be satisfied." (SRCD3.2.1.1.1-4)
5. "… CMIS shall satisfy the EDR Thresholds associated with cloudy conditions under all measurement conditions …" (SRD SRDC3.2.1.1.1.1-1)
6. "Soil Moisture [is defined as] Moisture in the soil within the zone of aeration in cm/m (cm of water per meter of soil depth), including water vapor present in soil pores." (SRD Appendix A, section 10.1, p. A-13)

Also note that the CMIS system consists "of all ground and spaceborne hardware and software necessary to perform calibrated, microwave radiometric measurements from space and the software and science algorithms necessary to process … these measurement into a format consistent with the requirements of the assigned [EDRs]." (SRD, section 3.1.1)

3.2.2. Requirements interpretations

We infer the following statements as either direct consequences or clarifications of the SRD requirements stated above and take them as requirements to be satisfied by the soil moisture algorithm or to be addressed through algorithm performance evaluation:
1. "A surface layer over soil" means water present in puddles or larger temporary or permanent open water bodies. It does not mean water present in a snow, ice, vegetation, or other type of layer in any phase.
2. "Horizontal coverage[:] Land" excludes the global ocean but includes inland water bodies (for example, lakes, seas, rivers, and wetlands). Water bodies are included explicitly to provided consistency with 1 (above) while avoiding the need to make subjective definitions for "temporary" and "permanent" or large and small water bodies.
3. As a limiting condition, a "bare soil" retrieval cell contains nothing on the ground that obscures the soil or standing water surface.
4. "Known soil types" are characterized by existing soil texture maps.
5. Soil moisture measurement for "vegetated terrain" is required where vegetation amount (measured in terms of exposed soil fraction or cell-average canopy microwave transmittance) permits adequate sensitivity to soil moisture. Conditions where these criteria are not met are documented in section 5.1.

3.2.3. Derived requirements imposed by other EDR algorithms

No additional requirements on the soil moisture algorithm have been derived from SRD requirements for other EDRs or from the requirements of other CMIS algorithms.

3.3. Historical and background perspective of proposed algorithm

The retrieval of soil moisture by microwave radiometry is based on both theoretical and experimental work extending back more than 30 years. Nevertheless, there is no history of either global operational retrievals or validated long-term retrospective retrievals of soil moisture from spaceborne microwave radiometric instruments from which we may adapt a retrieval algorithm for CMIS. Furthermore, the EDR product specified by the requirements above has attributes and performance criteria that either constrain the retrieval algorithm in some way or require modification of existing research algorithms. The 40 km horizontal cell size requirement, for example, means that 6 GHz channel inputs will include a combination of spatial noise and resampling errors. Also, the requirement for surface water inclusion in the spatially integrated EDR product means that the algorithm design must be robust where permanent, discontinuous surface water is abundant or there is flooding. The following items summarize some of the defining attributes of the CMIS system, requirements, and retrieval approach:

1. The CMIS system will perform atmosphere temperature and water vapor sounding using channels that are either completely or partially insensitive to near-surface soil moisture. The soil moisture algorithm will ingest surface emissivities and effective temperature (LST) retrieved by the Core Module atmospheric algorithm (see *ATBD for the Core Physical Inversion Module*, AER, 2000). The Core Module retrieval adapts as needed to emissivity changes caused by surface moisture variability, among other things.
2. Core Module products will be available at both 40 and 50 km resolutions with the exception of 6 GHz emissivities which cannot be retrieved at 40 km due to 6 GHz sensor spatial resolution (see Table 3-2).
3. The algorithm can satisfy bare soil performance requirements using 10 GHz 40 km emissivities from the Core Module (with some tolerance of light vegetation cover.) To extend its measurements to more vegetated areas, the algorithm uses both 6 GHz and 10 GHz inputs. Because of additional error sources inherent in the 6 GHz data, this approach may compromise bare soil retrieval performance to achieve wider soil moisture retrieval coverage. Additional algorithm quality control measures must be applied to minimize error sources and maximizes the benefit of 6 GHz inputs.

Lower microwave frequencies have advantages in soil moisture sensing because (a) surface roughness and heterogeneity effects and atmospheric and canopy attenuation are minimized, and (b) the soil surface layer affecting emission is maximized thereby increasing the effective soil moisture sampling depth (Jackson and Schmugge, 1989). Primarily for these reasons, many studies have focused on development of a soil moisture remote sensing capability at 1.4 GHz or L band (Jackson et al., 1999). Yet serious practical size limitations have kept L band channels off operational satellites with microwave radiometers. (The footprint size for a hypothetical CMIS 1.4 GHz channel would be about 300 km with the current reflector provided that room could be found for a properly sized feed horn.) The higher-frequency (19-85 GHz) and higher-resolution (70-15 km) channels available from SSM/I have been shown to be sensitive to water bodies, flooding, and surface moisture (Sippel et al., 1994; Neale et al., 1990) but are in general too sensitive to vegetation and atmospheric conditions to be used for robust and consistent soil moisture measurements.

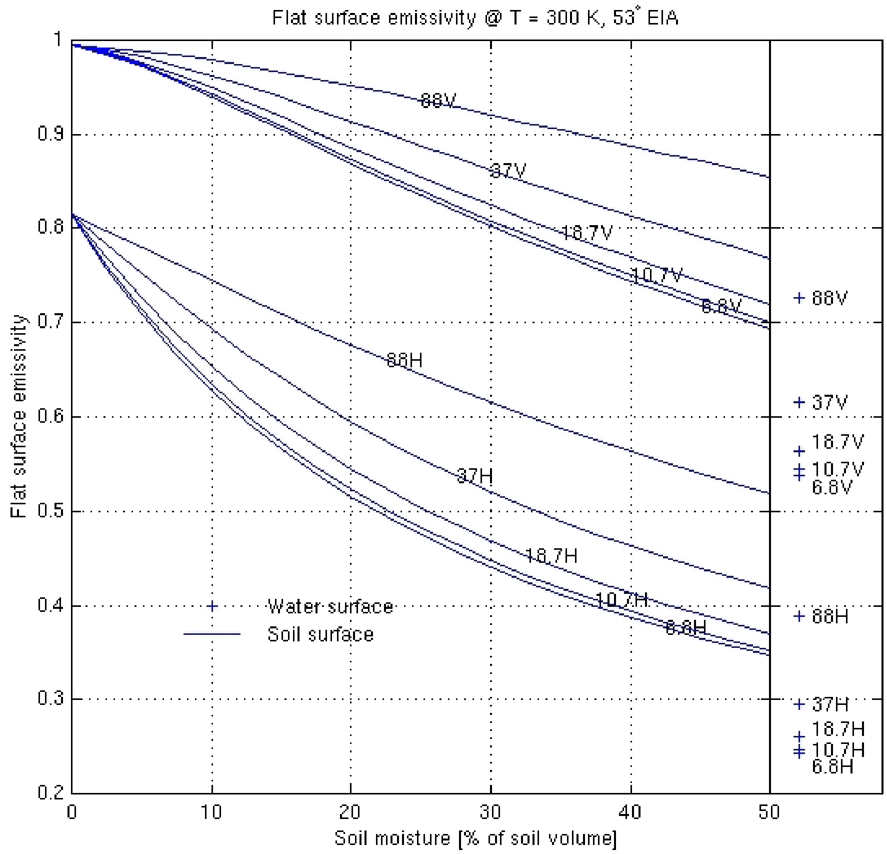
Low frequency sensors include the Nimbus-7 SMMR instrument (1978-1987) with 6.6 and 10.7 GHz channels, the TRMM TMI instrument (1998-present) with 10.7 GHz channels, and the AMSR instrument with 6.9 and 10.7 GHz channels slated for launch on EOS-Aqua (Spring 2001 launch) and ADEOS II (Spring 2002). Although there are fewer studies directly addressing soil moisture sensing at these frequencies than at L band, a substantial body of experimental and theoretical work exists to support a soil moisture measurement capability with 6 and 10 GHz channels. The key studies include Wang (1985), Choudhury and R. E. Golus (1988), Kerr and Njoku (1990), Owe et al. (1992), van de Griend and Owe (1993), van de Griend and Owe (1994), Calvet et al. (1996), Njoku and Li (1999), Vinnikov et al. (1999), and Ahmed (1999). In addition, the EOS-Aqua AMSR ATBD (Njoku, 1999) describes a method for retrieving soil moisture and other land parameters similar to our CMIS algorithm: For example, the CMIS physical model is closely related to AMSR's but the solution method and handling of open water differ.

Because of the absence of soil moisture retrieval operational heritage, the CMIS algorithm will benefit from both pre- and post-launch validation efforts. The similarity of AMSR's window-channel set to CMIS suggests that AMSR brightness temperatures will provide the best opportunity for pre-CMIS tests of the CMIS soil moisture algorithm. Similarities between the CMIS and AMSR physical models should also simplify the adaptation for CMIS use of datasets and procedures derived during AMSR test and validation efforts. Preliminary retrieval tests of the CMIS soil moisture algorithm with TMI 10 GHz data and SMMR 6 and 10 GHz data are described in sections 5.5.1 and 5.5.2, respectively.

3.4. Physics of problem

Microwave radiometric soil moisture retrieval is based on the strong dependence of soil's dielectric constant on the amount of liquid water present in soil pores. Despite variations in soil composition, porosity, and temperature, soil moisture is the dominant determinant of dielectric constant temporal variability for most soils. If the soil were a flat homogeneous half-space observed without vegetation, atmosphere, or other obstructions, then plane-wave soil emissivity could be expressed exactly by the so-called Fresnel expressions (see eqs. (3)-(4) below) and high-precision soil moisture could be inverted from simultaneous observations of microwave brightness temperature and thermometric temperature. Flat surface soil emissivities are plotted in Figure 3-1 using the Fresnel expressions and the Dobson soil dielectric properties parameterization (Ulaby et al., 1986). The plot shows that the sensitivity of emissivity to soil moisture content is highest for lower frequencies and horizontal polarization, and that flat open water emissivity is 0.10-0.16 lower than the most saturated soils. Over the full range of unsaturated soils (about 50%), the 6 and 10 GHz H-pol. emissivity sensitivities to soil moisture are about 0.094 per 10% soil moisture

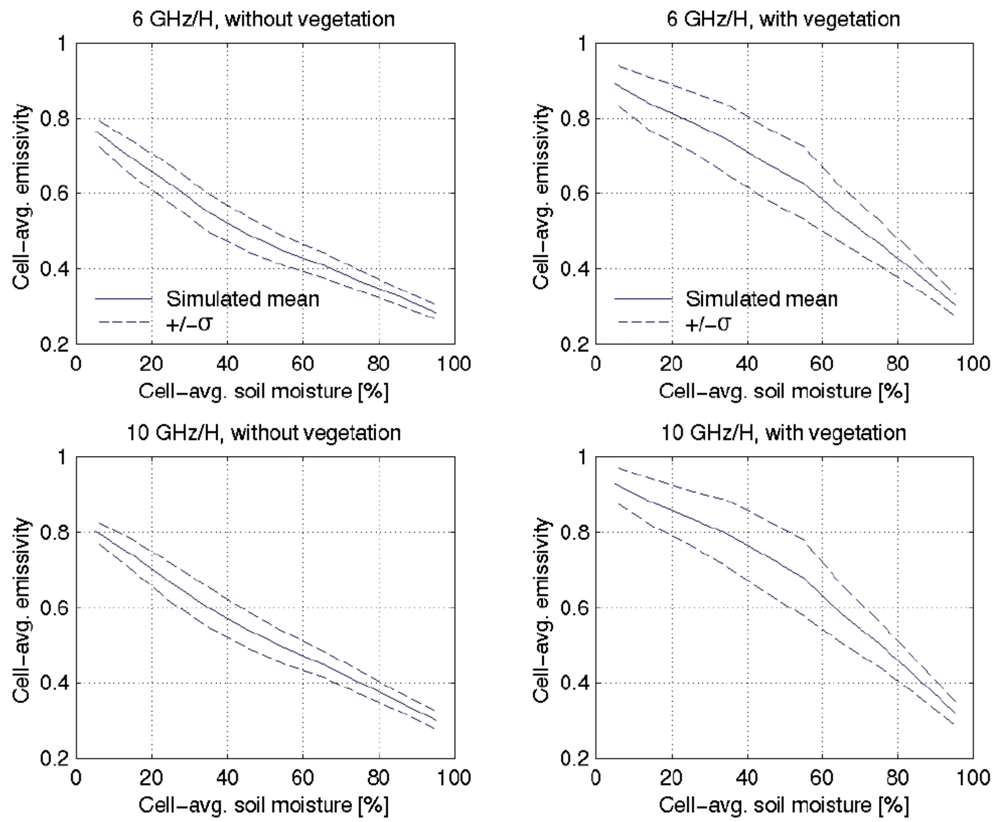
Figure 3-1: Flat-surface homogeneous soil and water emissivity model



Natural soils are neither flat nor homogeneous and are typically covered by some amount of vegetation and/or standing water and an overlying atmosphere. In addition, surface temperature and emissivity must be simultaneously retrieved as a first step to soil moisture measurement. Two factors will help minimize the impact of environmental noise. First, of the channels plotted in Figure 3-1, those most sensitive to soil moisture (6 and 10 GHz) are least sensitivity to atmospheric interference. Second, as discussed in the *ATBD for the CMIS Core Physical Inversion Module* (AER, 2000), atmospheric state and surface temperature are coupled so channels with good atmospheric sensitivity can aid the retrieval of surface temperature while minimizing sensitivity to surface emissivity variation. Consequently, it is surface condition variability not atmospheric or temperature effects that make the largest contribution to soil moisture retrieval uncertainty.

Figure 3-2 shows simulated cell-average emissivities as a function of cell-average soil moisture for horizontal-polarization 6 and 10 GHz channels. (Note that cell-average soil moisture includes open water according to equation 10 below.) The plots show cases with no vegetation as well as cases with variable sparse vegetation cover (that is, ranging from 0-1.5 kg/m^2 vegetation water content). The dashed lines delineate the +/-σ range of emissivity variability when roughness, soil composition, standing water, temperature, and vegetation (where present) factors are randomly varied over prescribed ranges. (See section 5.2.1 for description of the simulation environment.) There is little quantitative similarity to the curves in Figure 3-1. The presence of open water, roughness, and vegetation distort the mean curve and parametric variability add noise comparable to (or greater than in the case with vegetation) 0.09 emissivity sensitivity per 10% soil moisture. Environmental noise is highest where the soil is saturated and roughness and vegetation variability have their greatest effects. Cases dominated by open water (the simulated soil saturates at 50%) have decreasing variability because open water emissivity variability (affected only by wind speed and temperature) is lower than that of bare or vegetated ground.

Figure 3-2: Natural cell-average emissivity sensitivity to soil moisture



3.5. Instrument characteristics and derived requirements

CMIS is a conically-scanning microwave radiometer with window channels—frequencies chosen to avoid atmospheric absorption lines—around 6, 10, 19, 37, and 88 GHz and atmospheric sounding channel families around 23, 50-60, 60, 166, and 183 GHz. The instrument rotates continuously at 31.6 rpm on an axis perpendicular to the ground taking observations along nearly semi-circular arcs centered on the satellite ground track. Successive arcs scanned by a single sensor channel are separated by about 12.5 km along-track (depending on satellite altitude.) Calibration data is collected from a source (hot) and deep-space reflector (cold) viewed during the non-earth-viewing portion of the rotation cycle. Each observation (or sample) requires a finite sensor integration time which also transforms the sensor instantaneous field of view (IFOV)—the projection, or footprint, of the antenna gain pattern on the earth—into an observation effective field of view (EFOV). The start of each sample is separated by the sample time which is slightly longer than the integration time. The sample time is t_s = 1.2659 ms for all channels with the exception of 10 GHz (exactly $2t_s$) and 6.8 GHz ($4t_s$). All samples fall on one of three main-reflector scan-arcs or a single secondary-reflector scan arc (166 and 183 GHz channels families only).

Sensor sample processing (described in the *ATBD for Common EDR Processing Task*, AER, 2000) creates composite measurements which are the spatial weighted superposition of a contiguous group of sensor samples. Although not exact, the process is designed to match observations from different channels to a single reference footprint: The composite fields-of-view (CFOVs) from different channels are more closely matched and collocated than the corresponding EFOVs. In addition, because sensor noise (as measured in NEDT) is both random and independent between samples, the effective NEDT of composite footprints may be reduced (amplified) if the square-root of the sum of squared sample weights is less than (greater than) one. The soil moisture algorithm uses data processed to match both 40x40 and 50x50 km reference footprints.

Table 3-2 lists specific characteristics relevant to the soil moisture EDR for each sensor channel. (Sounding channel families around 50-60 and 183 GHz are listed as groups. Other channels that are neither H or V pol. are not listed.) Channels that are applied to soil moisture retrieval are marked either as required to meet or approach threshold requirements (X) or used to meet or approach objectives (O). Many channel combinations that exclude some of those marked with an X will also meet threshold requirements. An example minimum channel set—one that meets all threshold requirements with the fewest channels—would include some but not all of the 19, 23, and 37 GHz channels (for LST and open water fraction retrieval) and the V-pol. 6 GHz channel and at one 10.7 GHz channel. (Only one of the 6 or 10 GHz channels is needed to meet performance requirement for *bare ground* soil moisture retrieval.) Additional channels above 37 GHz can enhance performance of the Core Module's LST product; additional 6 and 10 GHz channels can enhance performance in bare and lightly vegetated regions. See section 5.3 for more detailed estimates of performance degradation with limited channels sets.

Table 3-2: Instrument Characteristics and Soil Moisture Channel Applications

	SELECTED SENSOR CHANNEL SPECIFICATIONS														
Channel prefix	6		10		18		23		36		60VL	89		166	183V
Channel suffix(es)	V	H	V	H	V	H	V	H	V	H	A,…	V	H	V	A,B,C
Frequency range [GHz]	6.45-6.8		10.6-10.7		18.6-18.8		23.6-24.0		36.0-37.0		50-60	87.0-91.0		164.5-167.5	173.4-193.3
Soil moisture channel applications[1]	X	X	X	X	X	X	X	X	X	X	O	O	O	O	O
Single-sample NEDT [K]	0.47		1.2		1.3		1.1		0.66		2.8[2]	0.57		2.7	2.7[2]
40 km composite max/min NRF	3.7/		0.55/		0.14/		0.14/		0.15/		0.14/	0.15/		0.14/	0.14/
50 km composite max/min NRF	1.8/		0.23/		0.11/		0.11/		0.11/		0.11/	0.11/		0.11/	0.11/
Earth incidence angle	55.9		58.3		53.8		53.8		55.9		55.9	55.9		55.7	55.7
Cross-scan EFOV [km]	66.5		46.8		23.1		21.3		16.9		15.0	14.9		17.4	15.5
Along-scan EFOV [km]	40.1		24.9		14.2		13.3		10.8		8.2	8.3		9.6	9.6
Integration time [ms]	5		2.5		1.2		1.2		1.2		1.2	1.2		1.2	1.2
No. EFOV per scan															
Swath width [km]															

[1] X = channel required to meet or approach threshold; O = channel used to meet or approach objectives.
[2] Figures are for lowest frequency in set. For illustrative purposes only.

3.6. Requirements for cross sensor data (NPOESS or other sensors)

The present design of the soil moisture algorithm does not require any data from sensors other than CMIS.

The algorithm will accept surface temperature inputs from VIIRS (or a VIIRS-like sensor) in addition to the Core Module's surface effective all-band microwave emitting temperature. The algorithm computes the spatial-average value of the cloud-free VIIRS LST EDR product and re-maps it to the CMIS soil moisture cell. Expected temperature variance due to microwave-thermal IR sensing depth differences and IR measurement uncertainties (at 40 km scale) are also input to the algorithm. To be useful, the VIIRS LST product should have uncertainty performance at least as good as CMIS at 40 km. Section 5.2.1 describes tests in which the algorithm uses thermal IR sensor LST inputs while retrieving soil moisture from TRMM TMI- and VIRS-observed data.

3.7. Required, alternate, and enhancing algorithm inputs

3.7.1. CMIS Data and Product Requirements

Table 3-3: Inputs from other CMIS algorithms

CMIS Products	Usage
Spectral Emissivity from Core Module algorithm	-Primary soil moisture retrieval input -Required at 6 GHz (50 km HCS) and 10 GHz (40 km HCS), V and H polarization -Required at current time
Skin Temperature from Core Module algorithm	-Supports soil moisture retrieval -40 and 50 km HCS -Required at current time
Open water fraction from vegetation/surface type algorithm	-Adjusts cell emissivity for open water, provides open water component of soil moisture product -20 km HCS -Required at current time
Precipitation Flag from Core Module Algorithm	-Quality control input -Required at current time, 40 and 50 km HCS

The soil moisture algorithm imposes the following requirements on other EDR algorithms in order to achieve retrieval performance estimates reported here:

1. The vegetation/surface type EDR algorithm must retrieve an open water fraction product at 20 km horizontal cell size with 13% or better measurement uncertainty. (The soil moisture algorithm resamples this product to the 40 km soil moisture retrieval scale.)
2. LST EDR algorithm must retrieve a 40 km HCS LST product with 2.4 K or better measurement uncertainty.

The impact of these requirements on performance can be assessed from the error budget in Table 5-9.

3.7.2. Other NPOESS Sensor Data and Product Inputs

No sensor data or products are required from other NPOESS instruments.

3.7.3. External Data Requirements

Table 3-4: External data requirements

External Data	Usage
Surface Database	-Provides static surface data for algorithm branching -Data indicates if cell is dominated by combination of ocean, dense vegetation, urban, or snow or ice types or by other type for which soil moisture is retrievable

3.7.4. Alternate and Enhancing Data Sources

Table 3-5: Alternate and enhancing data sources

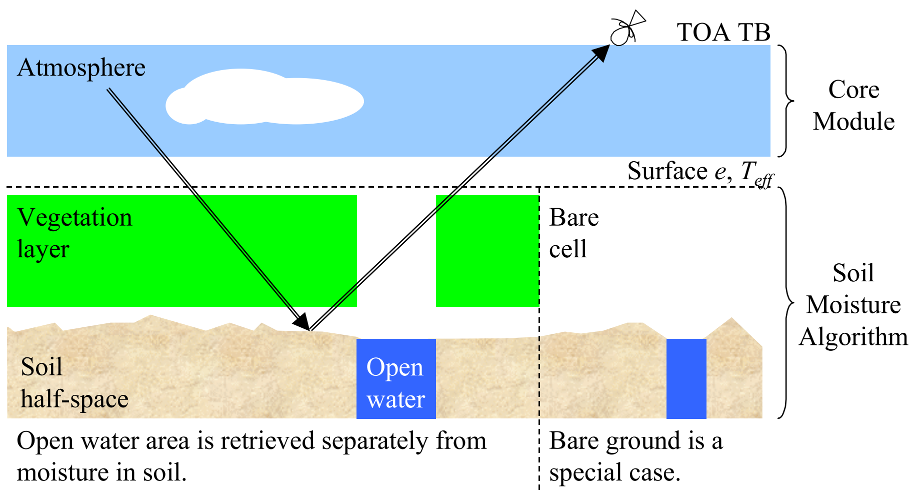
Data Source	Usage
CMIS: Vegetation/Surface Type EDR	-Augments static external surface database with more up-to-date data -Provides surface type for algorithm branching
CMIS: Past VWC retrieval database	-Reduces VWC retrieval noise by combining multiple observations of more slowly varying VWC
CMIS: 6 and 10 GHz TBs	-Alternatives to spectral emissivity inputs
VIIRS NDVI (or similar)	-Provides means of independently estimating VWC
VIIRS LST	-Augments skin temperature inputs
Soil type database	-Provides soil texture parameters for soil moisture forward model

4. Algorithm Description

4.1. Theoretical description of algorithm

We derive the soil moisture EDR based on the environmental system model diagrammed in Figure 4-1. The CMIS Core Physical Inversion Module removes atmospheric effects and retrieves surface effective emitting temperature T_{eff} and spectral emissivity e from top-of-atmosphere brightness temperature measurements. The Core Module uses a plane parallel model of the atmosphere whose lower boundary condition is parameterized by T_{eff} and e, where $e \equiv 1 - r$ and r is the surface specular reflectivity. A single background state and its error covariance matrix—tuned to global non-ocean conditions—constrain the retrieval. The Core Module also flags precipitation and passes atmospheric retrieval quality control values.

Figure 4-1: Schematic diagram of retrieval model representations



To more precisely retrieve soil moisture from emissivity in the presence of environmental noise, the soil moisture retrieval algorithm uses emissivities in both V and H polarizations at 6 and 10 GHz. Static data and other EDR products provide preliminary surface typing that determines if the surface is snow or ice covered, densely vegetated, masked by precipitation, or ocean (non-retrieval conditions). The surface type EDR algorithm also provides estimated open water cover fraction at 20 km scale which the algorithm resamples to 40 km. The algorithm estimates the emissivity of non-water covered (dry ground) areas of the cell using the water cover fraction and a temperature-dependent water emissivity model. (All surfaces and vegetation in the cell are assumed to be at T_{eff}.)

Dry ground soil moisture is retrieved by solution of a physical model (described below) with fixed parameters except soil moisture and vegetation water content. Like the Core Module, the soil moisture solver uses a mean background state and its error covariance to constrain the solution. The algorithm first performs the retrieval with a loosely constrained background that includes both bare and vegetated cases. If the retrieved vegetation amount is below a set threshold (e.g., 0.2 kg/m^2 VWC as a baseline), then the retrieval is repeated with more tightly constrained background statistics that limit the maximum VWC retrieval amount. If vegetation water content estimates are available from an external source (for example, previous CMIS or similar instrument retrievals) the algorithm will use the estimates as additional constraints on the retrieval.

Table 4-1 summarizes algorithm design trades leading to the baseline soil moisture algorithm design. The following sections give detailed descriptions of the mathematics of adopted trades and their role in the algorithm processing flow.

Table 4-1: Algorithm design trades

Trade Study	Baseline Decision	Basis/Benefit
Open water	Retrieve open water at 20 km HSR prior to dry ground soil moisture retrieval	Provides required retrieval of open water as component of soil moisture; higher frequencies are more sensitive to open water fraction than soil moisture
Spatial scale	Input 6 GHz emissivities with 50 km HSR; account for open water fraction at 50 km scale	Simulated benefit of 6 GHz inputs to soil moisture performance for vegetated terrain exceeds excess spatial error for 40 km product
Bare ground	Retrieve bare ground soil moisture as special case	Provides best performance for bare soil conditions in simulated retrievals; provides functionality for enhancing performance where external inputs identify bare soil
External vegetation inputs	Allow external VWC input	Provides enhancing capabilities where external estimates for VWC are available (e.g., based on NDVI or similar data)
Open water emissivity	Model water emissivity with water fraction-dependent wind speed parameter	Physical reasoning: Wind speed effect on water emissivity increases with size of water body

4.2. Mathematical Description of Algorithm

Table 4-2 defines soil moisture algorithm inputs and other variables used in this section. The following processing steps occur prior to soil moisture algorithm processing and are described in other documents: Derivation of CMIS brightness temperatures from raw data (*ATBD for SDR Processing*, AER, 2000); footprint matching and interpolation in the sensor reference frame (*ATBD for Common EDR Processing Tasks*, AER, 2000); Core Module retrievals of surface emissivities and effective emitting temperature (*ATBD for the Core Module*, AER, 2000); mapping of sensor-gridded data to an earth-grid (*ATBD for Common Tasks*); and retrieval of 20 km HCS open water fraction as part of the vegetation/surface type EDR algorithm (*ATBD for the Vegetation/Surface Type EDR*, AER, 2000).

Table 4-2: Definitions of Algorithm Input and Internal Model Symbols

Algorithm Inputs	
e_p	Frequency-dependent emissivity at polarization, p
T_{eff}	Wide-band surface effective emitting temperature, set equal to Core Module T_{skin} product
Other algorithm variables	
T_{Bp}	$= e_p T_{eff}$, surface emitted brightness temperature
f_w	Open water fraction in soil moisture retrieval footprint
$e_w(T_{eff})$	Open water emissivity estimate
T_{Bp}^{dry}	Derived dry-ground surface-emitted brightness temperature
f_{wi}	Open water fraction in N VST EDR retrieval cells
a_i	f_{wi} to f_w weighting coefficient
θ	Local earth incidence angle
n	Surface medium complex index of refraction
ε_w, ε_s	Water, soil complex permittivity
μ_a, μ	Air, surface medium propagation direction angle cosine
T_{se}, T_{ce}	Surface, canopy effective emitting temperature
τ	Vegetation opacity
b	$= b_o f/1.4$, vegetation opacity parameter
ω_p	Vegetation single scattering albedo
e_{op}	Planar soil surface emissivity
R_{op}, R_{sp}	Planar, rough soil surface reflectivity
Q	Surface reflectivity polarization mixing factor
h	Surface reflectivity roughness factor

Each of the following sections provides a mathematical description of a component of the CMIS soil moisture retrieval algorithm. Note that some components are repeated once or many times for each retrieval. Trivial components (namely, logical comparisons) are excluded. See Figure 4-2 for a diagram of the retrieval logic and processing flow.

Surface type estimation
Current surface type data are provided at 20 km nominal resolution by the Vegetation/Surface Type (VST) algorithm. Surface type retrievals are reported on an earth-grid with sample spacing that depends in general on position within the grid. The algorithm does not perform a retrieval if the type at the active soil moisture cell size (40 km) is more than 50% dense, urban, snow and ice, or ocean. To make this assessment, the algorithm calculates the fraction of excluded types in the active cell as the weighed sum of the M cells with excluded types. The weighting factors a_i are defined such that the combined spatial weight of N cells is similar to that of the other soil moisture inputs and the sum of N a_i equals 1, where N is the number of 20 km cells falling within the active soil moisture cell. The algorithm accesses a static surface database at the active cell size for surface type inputs if real-time data are unavailable.

Open water fraction adjustment

Like surface type, open water fraction inputs from the VST algorithm have a 20 km nominal resolution and are reported on an earth-grid with sample spacing that depends in general on position within the grid. We calculate the soil moisture footprint open water fraction, f_w, as the weighted average of N 20 km retrievals falling within the active soil moisture retrieval footprint (40 km),

$$f_w = \sum_N a_i f_{wi} \tag{1}$$

where the a_i are defined such that the spatial weight of f_w is similar to that of the other soil moisture inputs. Note that if the f_{wi} algorithm is a linear function of 20 km emissivities, then (1) is equivalent to applying the same function to the soil moisture footprint emissivities. The formalism of (1) is maintained to allow for non-linear water fraction algorithms and to focus surface type and f_{wi} calibration efforts on higher-resolution 20 km data. The algorithm accesses a static surface database at the active cell size for water fraction inputs if real-time data are unavailable.

The retrieved water fraction is used to estimate the surface-emitted brightness temperature of the non-water covered ('dry') part of the footprint:

$$T_{Bp}^{dry} = \frac{T_{Bp} - f_w T_{eff} e_w(T_{eff})}{1 - f_w}. \qquad (2)$$

The open water emissivity e_w is estimated as a function of temperature (estimated) and wind speed (assumed) using Wilheit's parameterization for a rough ocean surface modified to used Klein and Swift's water complex permittivity model. (See *ATBD for the Core Module* for more details.)

Retrieval after open-water adjustment

The dry-soil retrieval algorithm uses a non-linear physical approach based on Rodgers (1976). The algorithm finds an estimate $\hat{\mathbf{x}}$ of the true state vector by minimizing the cost function

$$J(\mathbf{x}) = (\mathbf{y}^m - \mathbf{y}(\mathbf{x}))^{\mathbf{T}} \mathbf{W} (\mathbf{y}^m - \mathbf{y}(\mathbf{x})) + (\mathbf{x} - \mathbf{x}_o)^{\mathbf{T}} \boldsymbol{\Gamma} (\mathbf{x} - \mathbf{x}_o) \qquad (3)$$

where: $\mathbf{y}^m$ is the vector of measurements and may include some or all 6.8 and 10.7 GHz surface-emitted brightness temperatures ($T_{Bp}{}^{dry}$), the effective emitting temperature, and, optionally, an external surface temperature measurement (from an infrared instrument, for example); $\mathbf{y}(\mathbf{x})$ is a physical model estimate (defined below) of the measurement vector for a given state vector $\mathbf{x}$; and $\mathbf{x}_o$ is a supplied background state vector. The state vector contains at a minimum sub-surface soil moisture and vegetation water content. The state may optionally include surface temperature and atmospheric parameters (if the algorithm inputs are top-of-atmosphere brightness temperatures) or just surface temperature if an external surface temperature measurement were provided. When a vegetation water content estimate is available from retrievals or a database, the VWC background state is set to the measurement and the corresponding element of $\boldsymbol{\Gamma}$ is reset appropriately. The weighting matrices $\mathbf{W}$ and $\boldsymbol{\Gamma}$ are specified further below.

The first term in $J(\mathbf{x})$ is the weighted sum of the squared differences between measurements and physical model-calculated predictions of the measurements based on a state vector. The second term is a weighted sum of the squared differences between a state vector and the supplied background state; it represents a penalty function that increases the cost for solution state vectors that deviate far from the background state. Although the penalty function may serve little purpose for problems like ours with poorly correlated state variables that span a broad range, the formalism is retained to provide a mechanism for incorporating prior estimates of vegetation water content into the retrieval where it is predictable and would otherwise be a significant error source in the soil moisture retrieval. The background state vector and the weighting matrices are empirically determined and may be changed depending on the retrieval situation (for example, horizontal cell size or the amount of vegetation or open water in the retrieval cell.) (See also EN #64 response.)

The algorithm's retrieved state vector is the one which minimizes (3); it is the maximum probability solution in a Bayesian approach for Gaussian error statistics where **W** and **Γ** are inverses of the covariance matrices for measurement and background state noise, $\mathbf{S}_{\varepsilon}^{-1}$ and $\mathbf{S}_{\mathbf{x}}^{-1}$. The algorithm implements a Newton iteration procedure whose solution vector at step n is (Rodgers, 1976):

$$\mathbf{x}_n = \mathbf{x}_{n-1} + \mathbf{H}^{-1}[\mathbf{K}^{\mathbf{T}}\mathbf{S}_{\varepsilon}^{-1}(\mathbf{y}^m - \mathbf{y}(\mathbf{x}_{n-1})) + \mathbf{S}_{\mathbf{x}}^{-1}(\mathbf{x}_o - \mathbf{x}_{n-1})] \tag{4}$$

where $\mathbf{H} = \mathbf{K}^{\mathbf{T}}\mathbf{S}_{\varepsilon}^{-1}\mathbf{K} + \mathbf{S}_{\mathbf{x}}^{-1}$. The matrix **K** is the measurement forward model state vector gradient matrix which contains the partial derivatives of **y**(**x**) with respect to each element of **x** evaluated at $\mathbf{x}_{n-1}$ (initially, $\mathbf{x}_o$.) Iterations are terminated when either (a) the model-estimated measurement vector converges to within the measurement error of the input measurements or (b) **x** converges to $\mathbf{x}_{n-1}$ to within convergence criteria supplied for each state parameter.

Physical forward measurement model

The measurement model predicts the measurement vector from a supplied state vector using the following physical parameterizations. The land surface-emitted brightness temperature at the top of a lossy, scattering vegetation layer is modeled (after Njoku and Li, 1999) as:

$$T_{Bp} = T_{se}(1 - R_{sp})\exp(-\tau) + T_{ce}(1 - \varpi_p)[1 - \exp(-\tau)][1 + R_{sp}\exp(-\tau)] \tag{5}$$

where T_{se} is the effective soil surface temperature, T_{ce} is the effective canopy temperature (set equal to T_{se} in the retrieval), τ is vegetation opacity, and ω_p is an empirical vegetation single scattering albedo. The polarization-dependent rough (natural) surface reflectivity is modeled as:

$$R_{sp} = [(1 - Q)R_{op} + QR_{oq}]\exp(-h) \tag{6}$$

where Q is an empirical frequency- and roughness-dependent polarization mixing factor, R_o is the planar surface reflectivity (discussed below), q signifies the polarization orthogonal to p, and h is an empirical frequency and roughness-dependent reflectivity reduction factor. Vegetation opacity is modeled as:

$$\tau = b(f)w_e / \cos\theta \tag{7}$$

where w_e is the column-integrated vegetation water content (VWC) for predominantly non-woody vegetation, $b(f) = b_0 f/1.4$, and f is frequency in GHz. (See also EN #66 response.)

Idealized flat soil surface emissivities e_{op} are given by the equations of plane-wave reflection at a planar boundary between two semi-infinite media (the so-called Fresnel expressions, Ulaby et al., 1981):

$$e_{ov} = 1 - \left|\frac{\mu - n\mu_a}{\mu + n\mu_a}\right|^2 \tag{8}$$

$$e_{oh} = 1 - \left| \frac{\mu_a - n\mu}{\mu_a + n\mu} \right|^2 \tag{9}$$

where $\mu_a = \cos(\theta)$, $\mu = \cos(\text{asin}(\sin(\theta)/n_r))$, $n_r = \text{Re}\{n\}$, n is the soil medium's complex index of refraction (square-root of the complex permittivity ε), and θ is the local earth incidence angle. Then R_{op} equals 1-e_{op}. Subsurface soil moisture enters the forward model through the soil complex permittivity parameterization. For soil complex permittivity ε_s, the soil moisture algorithm uses the Dobson soil dielectric mixing model as described by Ulaby et al. (1986) with the complex permittivity of water ε_w given by the temperature and frequency dependent Debye equation for pure water (Ulaby et al., 1986). Alternatively, the model of Wang and Schmugge (1980) could be used. The choice of these or other alternatives is subject to future algorithm calibration and validation (see section 5.4.) These or any other soil permittivity parameterization will be dependent on both soil moisture and temperature through the temperature dependence of ε_w. The depth of the soil layer represented in this model is dependent on the sensor frequencies, soil types, soil moisture content, and other factors. Section 4.3 describes estimation of the retrieval vertical cell size performance for the CMIS soil moisture retrieval algorithm.

Cell soil moisture calculation

The state vector solution (4) gives an estimate of the subsurface soil moisture m_e of the water-free portions of the retrieval cell. The soil moisture of open water is 100 cm/m by definition. The retrieval cell-average soil moisture—that is, the EDR definition of soil moisture given in section 3.2.2—is the weighted average of open water and water-free portions of the cell:

$$m_{cell} = 100 f_w + m_e(1 - f_w)\,. \tag{10}$$

Algorithm internal parameter settings

There are four free variables to be retrieved or input to the algorithm: f_w, T_{se}, w_e, and subsurface soil moisture m_e. (Cell soil moisture is also retrieved but as a post-processing step (10) dependent only on other retrievals.) The remaining variables are algorithm control parameters subject to calibration, which is discussed in more detail in section 5.4. Prior to comprehensive calibration, we use a simulation environment—described more in section 5.2.1—for setting algorithm parameter values. Table 4-3 summarizes the range over which each free variable and physical model parameter is varied in the simulation. Free variables vary over their natural ranges except VWC, which is limited to light vegetation conditions only. For hypothetical situations in which either open water fraction or vegetation cover is known to be zero, the algorithm sets f_w or w_e to zero, respectively, while retrieving the remaining variables.

The simulation varies other physical variables (the algorithms internal parameters) over wide natural ranges as inferred from the field and satellite measurements reported in the literature (Njoku and Li, 1999; Wang and Choudhury, 1981; Wang et al., 1983; Kerr and Wigneron, 1995; LeVine and Karam, 1996; Pampaloni and Paloscia, 1986; Jackson and Schmugge, 1991). Internally, these parameters are set to their midpoints in the retrieval algorithm. The resulting simulations are meant to yield performance estimates with ample error margins. We expect most environment conditions to have more benign physical variability such that one-time local, regional, or surface-type specific parameter calibration can provide significantly better parameter knowledge than that allowed for in simulation (for example, Njoku and Li, 1999). TMI real data tests in section 5.5.1 demonstrate algorithm execution with the internal parameters adjusted to better fit forward model measurement estimates to sensor observations. Section 6 discusses algorithm calibration and validation in more detail and section 5.4 discusses analysis constraints, limitations, and assumptions.

Table 4-3: Algorithm Simulation Environment Variables and Parameters

Algorithm Free Variables	Simulation Range	Algorithm Output Status		
Soil Moisture, m_e [cm/m]	0 – 50	Retrieved		
Open Water Fraction, f_w				
Cases with open water:	0-1	Retrieved		
Cases without open water:	0	0		
Surface Temperature, T_{se} [K]	273 – 320	Retrieved		
Canopy Temperature, T_{ce} [K]	T_{se} + 10 K noise	Retrieved = T_{se}		
Vegetation Water Content, w_e [kg/m^2]				
Vegetated cases:	0 – 1.5	Retrieved		
Unvegetated cases:	0	0		
Algorithm Internal Parameters	**Simulation Range**	**Algorithm Internal Value**		
Soil Roughness Parameters		Simulation Retrievals	TMI Retr.	SMMR Retr.
Q @ 6.8 GHz	0 – 0.12	0.06	0.03	0.09
Q @ 10.7 GHz	0 – 0.3	0.15	0.075	0.11
h @ 6.8 GHz	0 – 0.25	0.125	0.0625	0.11
h @ 10.7 GHz	0 – 0.4	0.2	0.1	0.19
Vegetation Parameters				
b_o	0.07 – 0.12	0.095		
w_o	0 – 0.15	0.075		
Soil Parameters				
Soil sand fraction	0.25 – 1.0	0.6		
Soil clay fraction	0 – 0.2	0.1		
Soil bulk density [kg/m^3]	1,400 – 1,600	1,500		

Covariance matrices and background state vector

The simulation environment is also used to establish mock databases from which we derived the covariance matrices, $\mathbf{S}_\varepsilon$ and $\mathbf{S}_\mathbf{x}$, and background state vector $\mathbf{x}_o$ appearing in (4). The elements of the measurement noise covariance matrix $\mathbf{S}_\varepsilon$ are $E[(y_i - \bar{y}_i)(y_j - \bar{y}_j)]$ where y_i is the i^{th} element of the measurement vector. The means and covariances are calculated for bare and vegetated scenarios from an ensemble of 3000 simulated realizations of the forward measurement model; for each realization, free and internal algorithm variables are randomly selected from uniform distributions over the simulation ranges in Table 4-3 and measurement noise (e.g., NEDT from Table 3-2) is added to the model's surface emitted brightness temperatures.

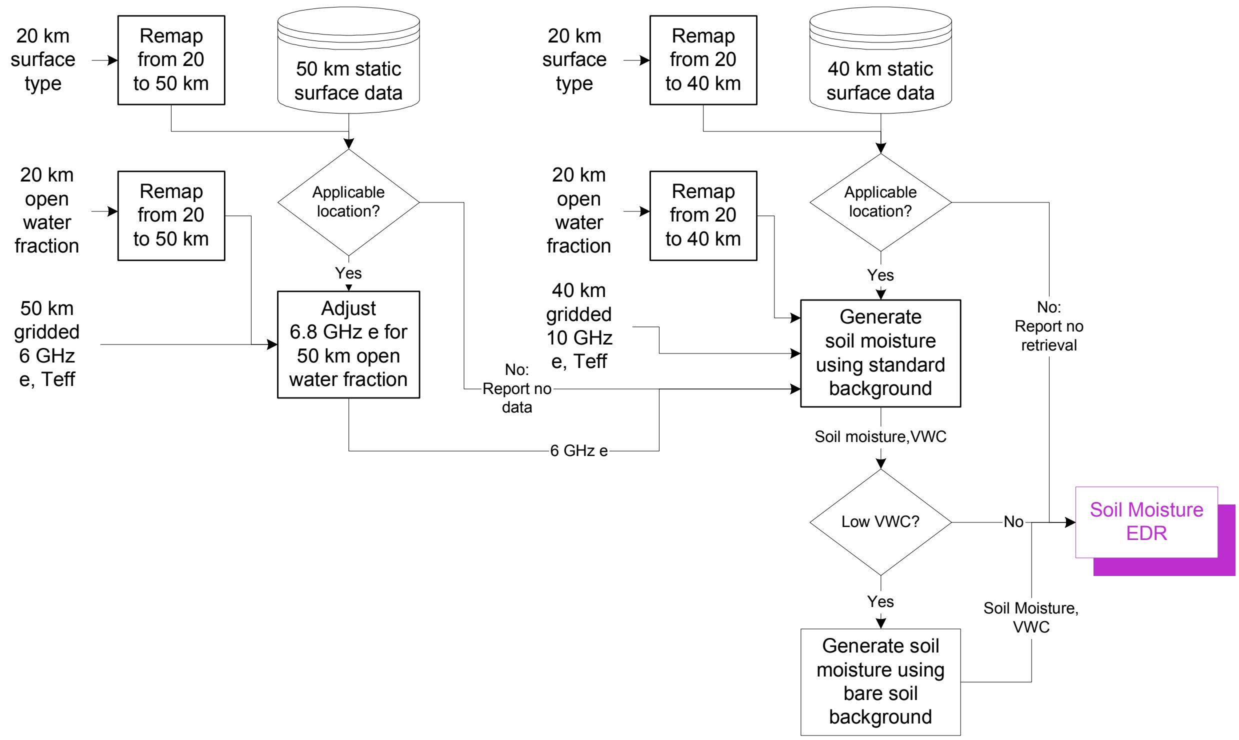
When the VWC retrieval is below a set threshold (0.2 kg/m^2 VWC as a baseline), the algorithm creates new background statistics based on the retrieved VWC and then repeats the retrieval. The new $\mathbf{S}_\varepsilon$, $\mathbf{S}_\mathbf{x}$, and $\mathbf{x}_o$ are the weighted combinations of their bare- and vegetated-scenario values. The baseline weighting factor is the cube root of the ratio of retrieved-VWC over threshold-VWC. In practice, this provides for smooth horizontal transitions between vegetated and bare regions as demonstrated with TRMM TMI data in section 5.5.1.

4.3. Algorithm Processing Flow

4.3.1. Processing Flow for CMIS Soil Moisture Algorithm

Figure 4-2 shows the processing flow for the retrieval algorithm. Section 3.4 describes algorithm physics and section 4.2 gives the algorithm's mathematical description.

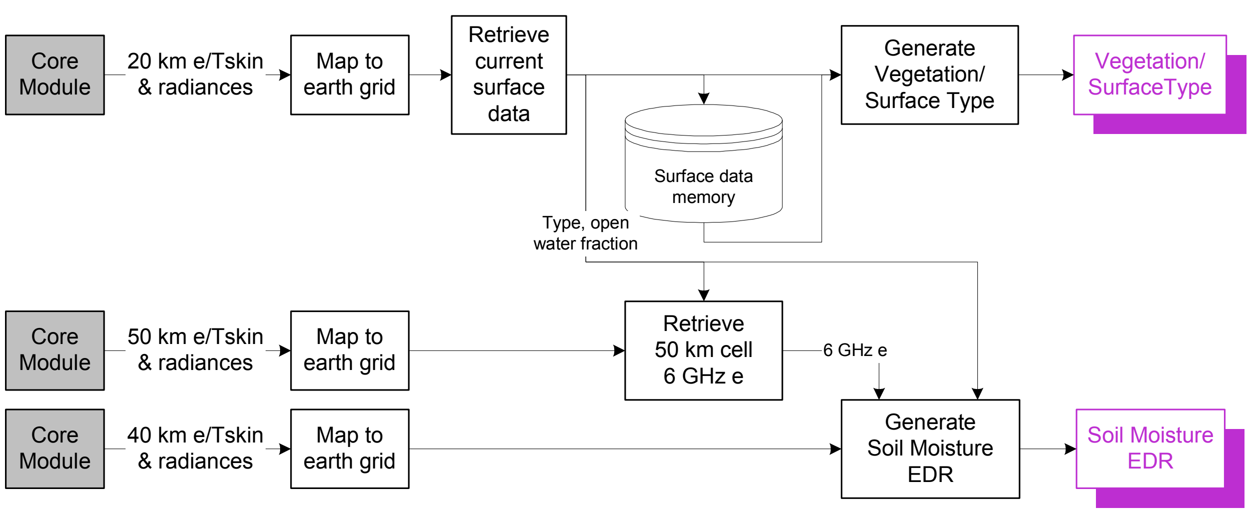
Figure 4-2: Soil Moisture algorithm detailed processing flow diagram



4.3.2. Relationship to Overall CMIS Processing Flow

Figure 4-3 shows the portion of the overall CMIS processing flow that includes Soil Moisture EDR retrieval. Note that only algorithm inputs that flow from real-time CMIS operations are shown.

Figure 4-3: Portion of the overall CMIS processing flow including Soil Moisture EDR



4.4. Algorithm inputs summary

The table below summarizes the input data used by the soil moisture algorithm. Input data requirements are described in more detail in section 3.7.

Table 4-4: Soil Moisture – Input Data Description

Input Data	Range
Emissivities @ 6V, 6H, 10V, 10H	0-1
Skin temperature	>0 K
Open water fraction	0-1
Static surface type	One of {ocean, dense, urban, snow/ice, other}
VST EDR	One of {snow/ice, other}
Prior CMIS VWC	0-10 kg/m^2
Brightness Temperatures @ 6V, 6H, 10V, 10H	>0 K
External VWC (e.g., from NDVI)	0-10 kg/m^2
External LST	>0 K
Static soil type	(0-100% sand, 0-100% slit, 0-100% clay, 0-1 porosity)

4.5. Algorithm products summary

The table below summarizes the characteristics of the operational Soil Moisture EDR product. Additional products available from the algorithm at 40 km HCS include vegetation water content, open water fraction, and soil moisture in the dry-land portions of the retrieval cell.

Table 4-5: Soil Moisture – Operational Product Description

Parameter	Value
Range	0-100 %
HCS	40 km
Units	% (volumetric)
QC Flag	Low Quality Input Data, Missing Data
Surface Flag	Ocean (a), Ice/snow, Bare Soil, Light Vegetation, Heavy Vegetation, Other (No Retrieval) (b)

(a) Product will not be generated over oceans but will be generated over inland water bodies. All ocean cells will have "Missing Data" flag.

(b) Bare Soil: Retrieved VWC is less than 0.2 kg/m^2.
Light Vegetation: Retrieved VWC is 0.2 kg/m^2 < VWC < 1.0 kg/m^2.
Heavy Vegetation: Retrieved VWC is greater than 1.0 kg/m^2.
Other (No Retrieval): Urban or ice or snow types

5. Algorithm Performance

5.1. General Description of Nominal and Limited Performance Conditions

This section describes the nominal and limited performance conditions at which the threshold requirements can be achieved. Two SRD sections address special conditions. SRDC3.2.1.1.1-4: "In the event the requirements for an EDR cannot be fully satisfied, the contractor shall identify the requirements which are not fully satisfied, and specify the conditions when they will not be satisfied." SRDC3.2.1.1.1-5: "The contractor shall also specify the conditions under which it recommends delivering an EDR which is incomplete and/or of degraded quality, but which is still of potential utility to one or more users."

Table 5-1 describes the nominal conditions under which Threshold Requirements can be achieved.

Table 5-1: Soil Moisture – Nominal performance characteristics

Conditions needed to meet threshold requirements	Description	Comments/Characteristics
Surface condition	• VWC < 1 kg/m^2 • Cell combined fraction of snow or ice, urban, ocean < 50% • Heavy vegetation fraction < 20%	Vegetation, snow or ice, and urban surfaces blocks signal from soil surface. Ocean areas are excluded by definition. Nominal conditions allow any amount of open water in cell.
Atmospheric condition	• Clear or cloudy • Precipitation < 1 mm/hr	Precipitation blocks signal from surface
Topographic condition	• RMS altitude < 300 m	Incidence angle variation with high relief increases retrieval error
Radio frequency interference (RFI)	• Undetected 6 GHz RFI < 5 K • Detected 6 GHz RFI > 5 K and VWC < 0.2 kg/m^2	Potential exists for RFI at 6 GHz. If detected, 6 GHz is not used and vegetation limits performance. If undetected, large RFI signal degrades performance.

Table 5-2 describes the Limited Performance Characteristics under specific conditions; Threshold Requirements may not be entirely achieved under these conditions.

Table 5-2: Soil Moisture – Performance under limited performance conditions

Conditions	Description	Comments/Characteristics
Medium-heavy vegetation cover	1.0 kg/m^2 < VWC < 1.5 kg/m^2 or 0.2 < heavy veg. fraction < 0.5	Limited retrieval (degraded uncertainty)
Heavy vegetation cover	VWC > 1.5 kg/m^2 or heavy veg. fraction > 0.5	No retrieval
Precipitation	Precipitation > 1 mm/hr	No retrieval
High relief	RMS altitude > 300 m	Limited retrieval (degraded uncertainty)
Undetected RFI	6 GHz RFI > 5 K	Limited retrieval (degraded uncertainty)
Detected RFI	6 GHz RFI > 5 K and 0.2 < VWC < 0.5 kg/m^2 6 GHz RFI > 5 K and VWC > 0.5 kg/m^2	Limited retrieval (degraded uncertainty) No retrieval

5.2. Variance/Uncertainty Estimates

This section details soil moisture algorithm performance estimates for each performance metric assigned to the algorithm from the following SRD attributes: C*V40.2.6-4/Vertical Cell Size, 5/Vertical Reporting Interval, 7/Vertical Coverage, 8/Measurement Range*, and *9/Measurement Uncertainty*. The soil moisture algorithm simulation environment (described in section 5.2.1) is the sole source for quantitative performance estimates for these attributes. Additionally, real-data tests of with TRMM observations (described in section 5.5.1) contribute qualitative algorithm assessments where noted.

Of the remaining attributes, *1/Horizontal Cell Size* and *3/Horizontal Reporting Interval* are derived from the spatial properties of the sensor footprints, footprint compositing and interpolation performance, and grid definition, *6/Horizontal Coverage* is satisfied through the spacecraft orbit specification and algorithm definitions (that is, the retrieval is performed over land by definition), *10/Mapping Uncertainty* is satisfied by spacecraft stability and instrument pointing error requirements, and *11/Swath Width* is met primarily through spacecraft orbit and instrument specifications and footprint compositing and interpolation performance. For related algorithm performance assessments, see the *ATBD for Common EDR Processing Tasks* (AER, 2000). Note that Horizontal Cell Size is an explicit part of the assessment of measurement uncertainty and other algorithm retrieval performance metrics. That is, quantitative performance estimates are base on comparisons of simulated retrieved soil moisture and true cell-average soil moisture.

5.2.1. Algorithm Simulation Environment

The simulation environment includes a measurement simulator and the retrieval algorithm. Both the algorithm and the simulator use implementations of the forward physical model detailed in section 4.2 albeit with intentionally different parameter values. Randomly generated noise-added brightness temperature, surface temperature, and open water fraction realizations from the simulator are the only dynamic algorithm inputs in the simulation environment. Baseline performance estimates have been derived by comparing algorithm retrievals to simulator truth using this configuration. (See also EN #102 response.)

Table 4-3 summarizes the algorithm and simulation environment model parameter values. In contrast to the algorithm, which assumes fixed values for unretrieved model parameters, the simulator randomly generates physical realizations by selecting parameter values from uniform distributions over the ranges given in Table 4-3. As discussed in section 4.2, the simulator is meant to provide uncertainty estimate margin by creating a more stressing retrieval environment than that expected from nature. It does this by varying model parameters over wide ranges determined from experiments and physical limits. For example, simulated 10.7 GHz soil roughness h varies from 0 (physical minimum) to 0.4. We infer the upper limit from several sources: (a) Wang et al. (1983) derived h values of 0, 0.11, and 0.6 by fitting a model to ground-based measurements over smooth, slightly rough, and rough fields; (b) Njoku and Li (1999) found a value for h of 0.19 by calibrating a physical model similar to ours to SMMR data from a region of the Sahel; and (c) Retrievals tests with TMI presented in section 5.5.1 suggest a value for h near 0.1 for swaths in the Sahara while ruling out a value of 0.2 or greater due to non-convergence of measured and modeled brightness temperatures. In setting the limits on simulated h, we assumed from these data that natural roughness variability at 40 km scale is somewhat less than that found at field-scale but nevertheless may fall within wide natural bounds. Use of a 0-0.4 simulation range for h along with $h = 0.2$ in the algorithm implies that the algorithm is limited only to the knowledge that extreme roughness conditions are not present. Similar logic was used in setting simulation ranges for the other roughness, vegetation, and soil parameters.

5.2.2. Binning Categories

Variance and uncertainty estimates are stratified by reporting performance in bins. Each bin represents a range of values for a particular environmental condition. Table 5-3 lists the bin categories and the environment parameter range for each bin. Typically, when measurement uncertainty is reported as a function one of these parameters, the other parameters are held in their default bins (highlighted in the table). This keeps the number of uncertainty estimates at a manageable level. The default bin for soil moisture is the full parameter range, 0-100%.

Table 5-3: Measurement uncertainty environmental parameter bins

Bin Category	Parameter Range: Soil Moisture [%]	Open Water Fraction	VWC [kg/m^2]	Dense Vegetation Fraction	RMS Altitude [m]
Bin ranges	0-20	0	0	0	0
	20-40	0-0.2	0-0.5	0-0.2	100
	40-60	0.2-0.8	0.5-1	0.2-0.8	250
	60-80	0.8-1.0	1-1.5	0.8-1.0	275
	80-100				300
	0-100				500

Soil moisture, open water fraction, and vegetation water content have been described in earlier sections of the ATBD. (Soil moisture here includes the contribution of open water fraction as specified in the EDR definition.) Dense vegetation fraction is defined here as the amount of vegetation too dense to allow sensitivity to soil moisture at 6 or 10 GHz (that is, radiometrically thick). Dense vegetation fraction cannot be directly retrieved by the soil moisture algorithm but does contribute to VWC and high fractions may therefore be readily detected for product quality control purposes. Static surface type maps also provide dense vegetation cover information for quality control. RMS altitude is the in-cell root-mean-square variation in altitude relative to the cell mean altitude and is a measure of topographic roughness. In practice, RMS altitude or other measures of topographic roughness can be determined from standard digital elevation models and used in quality control.

5.2.3. Horizontal Cell Size Performance

By algorithm definition, the soil moisture EDR horizontal cell size is 40 km. Note that this is a defined characteristic of the soil moisture EDR report; any validating or calibrating truth data must represent a 40 km cell and estimated retrieval performance must account for errors in spatial representativeness of the brightness temperature data or retrieved quantities. The error budget in Table 5-9 explicitly accounts for spatial errors related to cell size. Cell size spatial errors are manifested in the 40 km retrieval product for two reasons: (1) The maximum dimension of the 6 GHz composite footprint is greater than 40 km and (2) even when the 3dB contours of a composite footprint match a square retrieval cell exactly, only about 60% of the observed brightness temperature signal originates from within the cell. Note that if the retrieval cell and sensor footprint matched exactly, the cell size error would be zero by definition but other spatial heterogeneity errors would remain. See the *ATBD for Common EDR Processing Tasks* (AER, 2000) for more details on spatial sampling error analysis.

5.2.4. Vertical Cell Size, Vertical Reporting Interval, and Vertical Coverage Performance

A range of soil depths affect soil emissivity and the radiative signals used to sense soil moisture. Radiative transfer calculations for idealized soils suggest that the emissivity sampling depth for soil moisture ranges from about 0.03λ (wetter soil) to 0.07λ (drier soil), where λ is the free space wavelength and 45° incidence angle is assumed (Wilheit, 1978). 6.9 and 10.7 GHz wavelengths are 4.3 and 2.8 cm, respectively, giving a sampling depth range of 0.8-3 mm by this method depending on frequency and soil moisture. Based on this analysis, we define the vertical cell size for soil moisture retrieval as a skin layer 2 mm thick. Note that this is a defined characteristic of the soil moisture EDR report; any validating or calibrating truth data must represent the 0-2 mm depth layer and estimated retrieval performance must account for any variance in actual soil moisture sampling depth. By algorithm definition, a single value of soil moisture is reported—that is, the vertical reporting interval requirement is "N/A" (not applicable)—and the vertical coverage is equal to the vertical cell size.

5.2.5. Measurement Uncertainty Performance

The following tables summarize measurement uncertainty estimates stratified for a variety of environmental conditions. Note that with open water fraction equal to zero, the maximum soil moisture is about 50%. The tables give measurement uncertainty results directly from the simulation environment (described in section 5.2.1) and with additional measurement budget adjustments (described in section 5.3). (See also EN #102 response.)

Table 5-4: Soil Moisture measurement uncertainty by soil moisture range

Surface Stratification Categories - Baseline Bins					No. in Sim. Bin	Meas. Uncertainty [%]	
Range [%]	Open Water Fraction	VWC [kg/m2]	Dense Veg. Fraction	RMS Altitude [m]		Simulation	Simulation + Budget Estimates
0-20	0	0.5-1	0	0	358	5.52	6.10
20-40	0	0.5-1	0	0	429	7.99	8.40
40-60	0	0.5-1	0	0	211	7.51	7.95

Table 5-5: Soil Moisture measurement uncertainty by VWC

Surface Stratification Categories					No. in Sim. Bin	Meas. Uncertainty [%]	
Range [%]	Open Water Fraction	VWC [kg/m2]	Dense Veg. Fraction	RMS Altitude [m]		Simulation	Simulation + Budget Estimates
0-100	0	0	0	0	3000	3.62	4.40
0-100	0	0-0.5	0	0	988	5.38	5.98
0-100	0	0.5-1	0	0	998	7.09	7.55
0-100	0	1-1.5	0	0	1014	14.37	14.60

Table 5-6: Soil Moisture measurement uncertainty by open water fraction

Surface Stratification Categories					No. in Sim. Bin	Meas. Uncertainty [%]	
Range [%]	Open Water Fraction	VWC [kg/m2]	Dense Veg. Fraction	RMS Altitude [m]		Simulation	Simulation + Budget Estimates
0-100	0	0.5-1	0	0	998	7.09	7.55
0-100	0-0.2	0.5-1	0	0	223	6.89	7.37
0-100	0.2-0.8	0.5-1	0	0	608	7.83	8.25
0-100	0.8-1.0	0.5-1	0	0	142	6.15	6.68

Table 5-7: Soil Moisture measurement uncertainty by dense vegetation fraction

Surface Stratification Categories					No. in Sim. Bin	Meas. Uncertainty [%]	
Range [%]	Open Water Fraction	VWC [kg/m2]	Dense Veg. Fraction	RMS Altitude [m]		Simulation	Simulation + Budget Estimates
0-100	0	0.5-1	0	0	998	7.09	7.55
0-100	0	0.5-1	0-0.2	0	197	8.15	8.56
0-100	0	0.5-1	0.2-0.8	0	605	19.10	19.28
0-100	0	0.5-1	0.8-1.0	0	196	26.58	26.71

Table 5-8: Soil Moisture measurement uncertainty by RMS altitude

Surface Stratification Categories					No. in Sim. Bin	Meas. Uncertainty [%]	
Range [%]	Open Water Fraction	VWC [kg/m2]	Dense Veg. Fraction	RMS Altitude [m]		Simulation	Simulation + Budget Estimates
0-100	0	0.5-1	0	0	998	7.09	7.55
0-100	0	0.5-1	0	100	1021	7.61	8.04
0-100	0	0.5-1	0	250	1021	8.72	9.10
0-100	0	0.5-1	0	275	1021	9.60	9.95
0-100	0	0.5-1	0	300	1021	10.72	11.03
0-100	0	0.5-1	0	500	1021	14.87	15.10

5.2.6. Measurement Range Performance

By algorithm definition, the allowed measurement range is 0-100% volumetric soil moisture. Table 5-4 and Table 5-6 demonstrate that measurement uncertainty performance meets the threshold requirement of 10% over the full measurement range. Results with TMI and SMMR data in sections 5.5.1 and 5.5.2 demonstrate that the full measurement range is achieved by the algorithm in practice.

5.3. Sensitivity Studies

Soil moisture retrieval error sensitivity to individual error sources is expressed in the error budget in Table 5-9. Using the simulation environment described in section 5.2.1, we eliminated each listed error source in turn by setting the relevant simulation parameters to their fixed values known to the algorithm. The resulting set of retrieval RMS error results represent the error reductions that might be realized without each error source. We then calculated the error contribution of each source by subtracting the squared error reduction result from the squared overall simulated uncertainty estimate. The overall simulated uncertainty estimate is the result with all error sources contributing. Note that the overall budget error includes additional non-simulated error sources described below. (See also EN #66 and #98 responses.)

Table 5-9: Soil Moisture retrieval error budget

Error Source	Error in Selected Bins [%]			Comments
	Baseline + 0 VWC	Baseline + 0.5-1 VWC	Baseline + 0.5-1 VWC + 0-100% water	
Surface temperature*	1.35	1.75	1.09	Includes LST & emissivity input error
Canopy temperature	0.00	1.83	0.00	
Atmosphere	0.00	0.00	0.00	Excludes atm. impact on LST error
Surface roughness	2.91	4.13	2.22	Largest term without open water
Vegetation parameters	0.00	3.33	1.71	Reflects uncertainty in model physics and parameters
Soil parameters	1.00	0.99	0.00	
TB measurement noise*	0.71	3.46	2.37	NEDT & footprint composite effects
Wind speed	0.00	0.00	0.77	
Open water fraction*	0.00	0.00	4.89	Largest term with open water
Algorithm	1.15	1.66	3.95	Alg. assumptions, convergence, etc.
In-cell heterogeneity	0.70	1.00	1.00	Budget estimate (Njoku et al., 1996; Galantowicz et al. 2000)
Off-cell heterogeneity	1.70	1.70	1.70	Budget estimates
6 GHz 50 km HSR	1.70	1.70	1.70	
Total Uncertainty Budget	4.40	7.55	7.84	(Root sum of squares)

Errors are from environment or model except * are measurement errors

The "algorithm" error source is calculated as the residual error when all other simulated sources have been accounted for. In addition to simulated errors, the budget includes estimates for spatial heterogeneity error contributions due to in-cell heterogeneity, off-cell heterogeneity, and the use of 50 km 6 GHz data in the 40 km soil moisture EDR retrieval. Off-cell heterogeneity errors are caused by the sensor partially viewing areas outside the retrieval cell where conditions may deviate from the in-cell average.

We attribute bare soil algorithm errors to algorithm assumptions designed to control convergence in the presence of multiple error sources. For vegetated soil, ambiguity between soil moisture and vegetation water content (VWC) is another algorithm error source. That is, a particular brightness temperature spectrum (including sensor noise) may have a multiplicity of possible soil moisture/VWC solution states. The retrieval algorithm weighs observational and background inputs based on their assumed error covariance attributes to derive the most probable solution regardless of ambiguities.

The shaded cells in Table 5-9 highlight the largest error terms for each environmental bin. For bare soil, soil roughness variability is by far the largest single error source, whereas with 0-0.5 kg/m^2 VWC vegetation it is closely followed by TB measurement noise and vegetation parameter variability. Open water fraction retrieval error dominates soil moisture errors with 0-100% open water in the retrieval cell. Note that the link between soil moisture retrieval error and vegetation amount is both strong—as shown above and in Table 5-5 and Table 5-7—and most significant globally.

Table 5-10 shows soil moisture retrieval error sensitivity to input data losses for the same three environmental bins as Table 5-9. To test the impact of missing 6 and 10 GHz data, we removed from the simulation environment input data stream each channel individually and as V/H-pol. sets. To test the impact of degraded LST/emissivity retrieval, we increased the simulated LST measurement uncertainty to 5 K—a conservative estimate of performance achievable reliably with multiple channel set combinations. The table gives the resultant simulation environment measurement uncertainty estimates plus the error budget adjustments discussed above.

Table 5-10: Measurement uncertainty in data-poor situations.

Data Availability Situation	Meas. Unc. in Selected Bins [%]			Comments
	Baseline + 0 VWC	Baseline + 0.5-1 VWC	Baseline + 0.5-1 VWC + 0-100% water	
Baseline	4.40	7.55	7.84	Assumes 1.8-2.4 K LST RMSE
No 6H data	4.74	7.64	8.25	
No 10H data	4.69	8.55	8.03	
5K LST RMSE	5.01	8.69	8.64	<5K LST RMS achievable with multiple redundancies
No 10V data	4.47	9.07	8.77	Line delineates cases better/ worse than 10% threshold
No 10V, no 10H	4.62	14.64	10.14	
No 6V data	9.14	14.91	11.85	6V absense has most impact on performance
No 6V, no 6H	9.84	23.54	13.87	

Table 5-10 demonstrates how algorithm performance degrades gracefully with reduced input data irrespective of environmental conditions and without any special tuning or reconfiguration of the algorithm. Converse, it shows that the algorithm takes full advantage of the data to refine the retrieval when the full channel set is available. Note that 10% threshold measurement uncertainty performance is met for vegetated conditions even when 6H, 10H, or 10V data are absent.

Table 5-11, Table 5-12, and Table 5-13 show the effects of top-of-atmosphere brightness temperature bias on measurement uncertainty performance. The tables give simulated measurement uncertainty estimates plus error budget adjustments as discussed above. Biases could come from direct sources like calibration error or RFI (radio frequency interference) or from environmental sources like in-cell precipitation or scattering (frozen) surfaces. These tables indicate general retrieval tolerance to biased data. The simultaneous effect that environmental sources may have on surface temperature and open water fraction retrievals are not included.

Table 5-11: Measurement uncertainty with 6GHz bias.

6 GHz TB Bias [K]	Meas. Unc. in Selected Bins [%]		
	Baseline + 0 VWC	Baseline + 0.5-1 VWC	Baseline + 0.5-1 VWC + 0-20% dense
-20- -16	14.22	28.61	32.89
-12- -8	8.14	23.38	21.27
-8- -4	5.83	17.50	15.90
-4- 0	4.28	8.78	9.90
Baseline	4.41	7.75	8.17
0-4	4.65	9.20	8.81
4-8	5.14	16.78	15.04
8-12	6.70	19.97	21.92
16-20	8.86	26.57	27.18

Table 5-12: Measurement uncertainty with 10 GHz bias.

10 GHz TB Bias [K]	Meas. Unc. in Selected Bins [%]		
	Baseline + 0 VWC	Baseline + 0.5-1 VWC	Baseline + 0.5-1 VWC + 0-20% dense
-20- -16	4.03	21.66	22.90
-12- -8	4.29	17.18	17.31
-8- -4	4.40	11.44	11.80
-4- 0	4.19	8.78	9.62
Baseline	4.41	7.75	8.17
0-4	4.43	8.69	8.08
4-8	4.68	11.85	14.86
8-12	5.21	18.46	18.76
16-20	6.14	24.70	23.51

Table 5-13: Measurement uncertainty with simultaneous 6 and 10 GHz bias.

Simultaneous 6 and 10 GHz TB Bias [K]	Meas. Unc. in Selected Bins [%]		
	Baseline + 0 VWC	Baseline + 0.5-1 VWC	Baseline + 0.5-1 VWC + 0-20% dense
-20- -16	11.76	18.57	18.38
-12- -8	7.45	12.00	11.64
-8- -4	5.60	9.64	10.57
-4- 0	4.51	7.20	8.80
Baseline	4.41	7.75	8.17
0-4	4.47	7.28	6.81
4-8	5.52	9.01	9.09
8-12	7.22	12.05	10.68
16-20	10.74	17.77	17.35

As suggested by Figure 3-2, positive emissivity or brightness temperature measurement bias will generally result in negative soil moisture retrieval bias. Emissive sources like RFI will lead to soil moisture underestimation while radiatively cooling precipitation may lead to overestimation. Errors are limited by the natural range of soil moisture. If soil moisture is assumed to vary uniformly from 0-50%—as it is in our simulations when open water is not present—then the worst case RMS error of 29% occurs when bias drives the physical algorithm to its 0 or 50% limit. In comparison, if the data are known to be biased, then substituting a climatological mean soil moisture—25% in our simulations—for the retrieved value would result in only 14.4% RMS error. (In practice, the local climatological mean may be an even better predictor of soil moisture in regions where soil moisture varies less than our intentionally stressing simulations.) A potential future enhancement of the algorithm is a simultaneous estimate of measurement uncertainty in detectable stressing conditions such as the presence of precipitation or RFI. A backup climatological or short-term average soil moisture estimate (based perhaps on accumulated CMIS retrievals) could be used instead of the current observation when predicted measurement uncertainty exceeds a given threshold such as the 14% RMS derived from our simulations.

5.4. Constraints, Limitations, and Assumptions

- Performance estimates in the preceding sections are based on retrievals from simulated data. Although this method assumes that the physical forward model is an accurate representation of the true land surface and atmosphere radiative system, it models the system with multiple free variables unknown to the retrieval algorithm and varying over broad ranges. Specifically, the simulator varies all the parameters in Table 4-3 with uniform distributions over their full simulation range. We assume that this is a more stressing test than natural conditions where the states may be distributed normally rather than uniformly with lower variance around global or regionally-determined mean values. The more stressing distribution is used because of uncertainty in the veracity of the physical model itself.

  The retrieval algorithm uses the physical model to find values for retrievable variables (soil moisture, temperature, and vegetation water content) such that the brightness temperatures predicted by the model match those measured by CMIS. The benefit of a physical model is that it relates multiple retrievable and internal model parameters in a way that is self consistent and consistent with observed physical non-linearities. Field experiments have demonstrated that the model can match measured brightness temperatures to within in situ measurement errors when model parameters are correctly specified (for example, Wang et al., 1983, Kerr and Wigneron, 1995). Retrieval trials with TMI and SMMR data given in sections 5.5.1 and 5.5.2 show that the model can match satellite-measured brightness temperatures over broad regions using a single set of model parameters. We conclude from these results that the physical model is adequate for the task of tying measurements to retrieved variables while meeting the basic criterion of simultaneous measured-modeled brightness temperature convergence for all 6 and 10 GHz channels.

In making measurement uncertainty estimates, we assume that the physical model can exactly represent a particular set of environmental conditions but that it *never does* because of uncertainty in the model parameters. In other words, we assume that the particular realization of the physical model parameters that is encoded in the retrieval algorithm represents a generic situation whereas the ensemble of cases randomly generated in the forward model measurement simulator represent realistic variability in the physical environment. Measurement uncertainty estimates are calculated from the retrieval errors realized for every case in the ensemble whether or not brightness temperature convergence is achieved. The soil moisture measurement is always in error regardless of model convergence because retrieval and simulation model parameters are never the same. However, cases where the model does not converge represent a more fundamental failure of the physical model and are likely to have the largest retrieval errors. As discussed in section 5.2.1, the use of uniformly distributed model parameters in the simulation environment adds margin to performance estimates by increasing the number of cases where simulation and retrieval model parameters differ greatly and sometimes cause non-converging cases.

- Center-of-scan is assumed for all NEDT values in the simulated retrievals (Table 3-2). Composite footprint NEDT is high at center of scan because of the lower density of sensor samples distributed on the earth's surface. NEDT is lower—and performance commensurately but only slightly better—at other positions in the scan excluding the near-edges where samples that might be used in footprint matching are unavailable. Total swath width performance give for this EDR includes only scan positions where composite footprint NEDT is low enough to meet requirements.

- As stated in section 3.7.1, performance estimates are based on the assumptions that (a) the vegetation/surface type algorithm retrieves open water fraction at 20 km HCS with 13% or better measurement uncertainty, and (b) the LST algorithm retrieves LST at 40 km HCS with 2.4 K or better measurement uncertainty. The impact of these assumptions on performance can be assessed from the error budget in Table 5-9. (See also EN #83 response.)

- Effects of heavy vegetation, urban areas, snow cover, frozen ground, precipitation, high topographic relief, and RFI will introduce errors into the retrievals when these conditions are not detected.

- Errors induced by differences between the defined EDR vertical cell size (0-2 mm) and actual sampling depth are assumed to be negligible. That is, we assume that on average there is little difference—relative to other error sources—between soil moisture sampled from 0-0.8 mm and 0-2 mm or between soil moisture sampled from 0-3 mm and 0-2 mm. (See section 5.2.4 for more details on sampling depth analysis.) This assumption should be reexamined when adequate validation data are available.

5.5. Algorithm Tests with Similar Sensor Data

5.5.1. TRMM TMI Retrieval Tests

This study assesses the robustness, self-consistency, required tuning, measurement range, and operability of the CMIS soil moisture retrieval algorithm. We adapted the CMIS soil moisture algorithm to derive soil moisture from top-of-atmosphere brightness temperatures measured by the TRMM TMI instrument. Table 5-14 summarizes relevant TRMM instrument characteristics. The soil moisture algorithm was functionally identical to that used in the algorithm simulation environment with the following exceptions: (a) the algorithm values for the soil roughness parameters Q and h were modified as noted below, (b) LST was estimated by either a linear empirical method tuned for SSM/I (McFarland, 1990) or by the TMI-adapted Core Module, as noted, and (c) no ocean-land flag was input so retrievals were performed over land and ocean. We used radiance data from the TRMM VIRS instrument to provided an independent estimate of LST using the algorithms listed in Table 5-14. TMI data preprocessing consisted of making composite footprints closely matching a 60 km circular footprint for all channels and then resampling the composite brightnesses to a 50 km earth-grid. VIRS radiances were converted to brightness temperatures and then resampled to a 2 km earth-grid.

The input data were mostly trouble-free except that TMI LST was under-estimated over water because the McFarland algorithm is tuned for higher-emissivity arid land. As a consequence, microwave emissivity over water was over-estimated and water cover fraction was systematically underestimated—for example, the estimate over open water was consistently 90%.

Table 5-14: TRMM TMI instrument characteristics.

	TRMM Microwave Imager (TMI)	Visible and Infrared Radiometer System (VIRS)
Heritage	SSM/I, conical scanning, 53° incidence angle	AVHRR
Channels	10.7V/H, 19.4V/H, 21.3V, 37V/H, 85.5V/H GHz	0.63, 1.61, 3.75, 10.8, 12.0 μm
Nominal resolution	60 km (after our footprint matching processing)	2.11 km nadir IFOV
Swath width	759 km	720 km
Parameters derived/algorithm	LST regression/McFarland, 1990	LST/Wan & Dozier, 1996 Cloud mask/10.7 & 3.7-10.7 μm empirical thresholds

Table 5-15 lists attributes of two test regions centered on Egypt/Sudan and Mali. We acquired two overlapping swaths from the same day for each region—one daytime, or early evening, and one nighttime. The overlapping regions allow for retrieval consistency checks with changing viewing azimuth, time of day, surface temperature, and sensor noise realization but little soil moisture change. Complete swaths are used to analyze solution convergence, self consistency, robustness, and measurement range.

Table 5-15: TRMM Test Scene Summary.

Description	Egypt/Sudan, Lake Nasser, Red Sea	Mali, Timbuktu, Niger River
Center coordinates	22N 37E	18N 1W
Day of year	159	332
Observation times	0440/2100 Local Solar Time	0320/1124 Local Solar Time
Range of surface conditions	Arid land, lake, sea, vegetation in hills or near water	Arid land, vegetation near river/wetlands only
Altitude	0-2000 m	200-750 m

Description	Egypt/Sudan, Lake Nasser, Red Sea	Mali, Timbuktu, Niger River
TMI soil moisture range	0-90 cm/m	0-7 cm/m

Figure 5-1 shows the EDR product retrieved on the morning and afternoon Egypt-crossing and Mail-crossing TMI swaths. The EDR product is qualitatively consistent in all the passes: Coastlines are clearly rendered, Lake Nasser (32E,23N) and the Niger River (4W,15N) stand out as wet zones, and the bulk of the deserts are dry. The retrievals are also consistent between passes in the same-day cross-over areas, as discussed further below. Note that the algorithm will return dry retrievals in densely vegetated areas as well as dry deserts, so there is no gradient in the images between the desert and vegetated areas (generally south of 15N). (See Figure 5-3 for VWC retrievals.)

Figure 5-1: TMI soil moisture EDR retrieval swaths

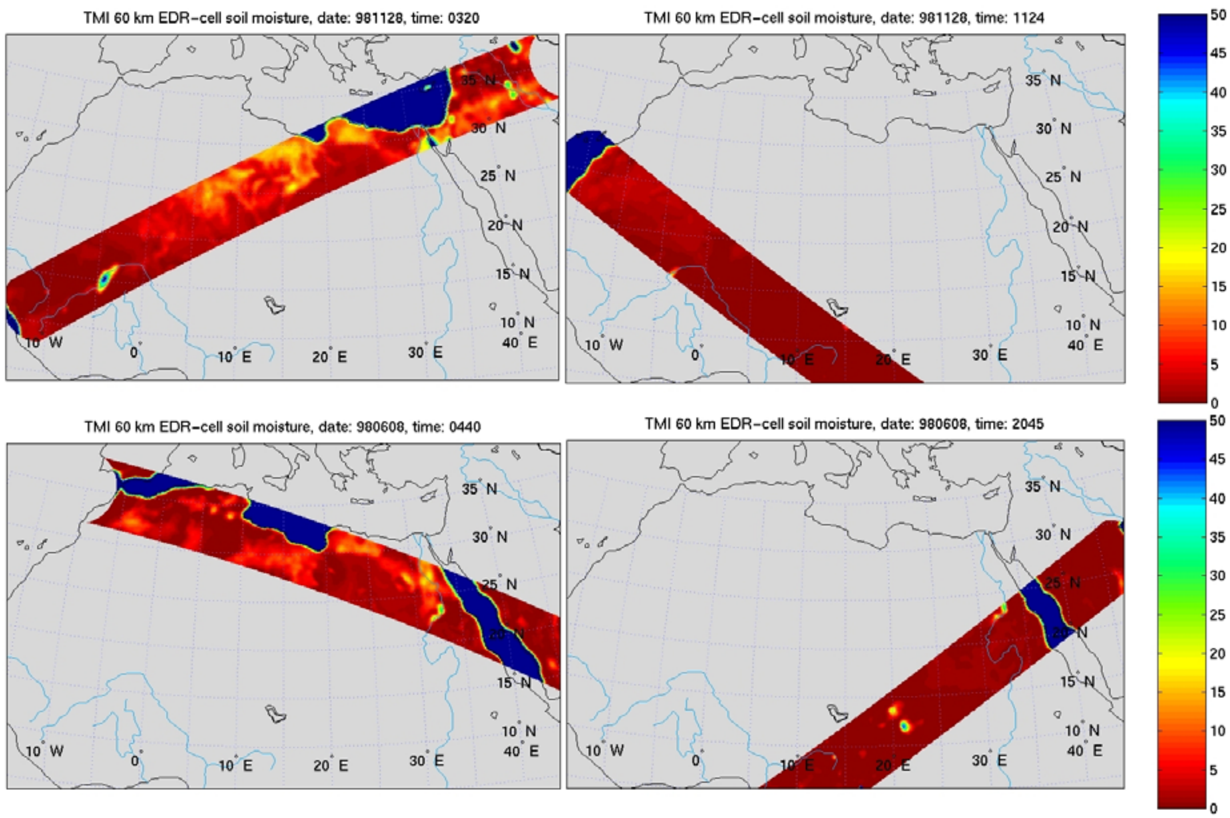


Figure 5-2 shows direct comparisons of same-day soil moisture retrievals in the two overlap regions (Egypt and Mali). RMS day night differences in the two regions are well within the retrieval variance predicted by simulation (e.g., Table 5-4). Day-night difference error sources and their expected magnitudes differ from those simulated or to be expected in global performance evaluation (e.g., see Table 5-9). Significant difference error sources include random instrument noise, geolocation, viewing geometry, and temperature and water fraction retrievals. Although global variability of roughness and vegetation parameters are not represented, errors from these parameters exist due to geolocation error and viewing geometry variability between observations. Temperature retrieval is a significant error source due to the use of a regression algorithm tuned to data from another instrument and region. Finally, water fraction retrieval difference errors should be significant due to sensitivity to the temperature retrieval and geolocation differences.

Figure 5-2: Comparisons of same-day soil moisture retrievals in Mali and Egypt regions

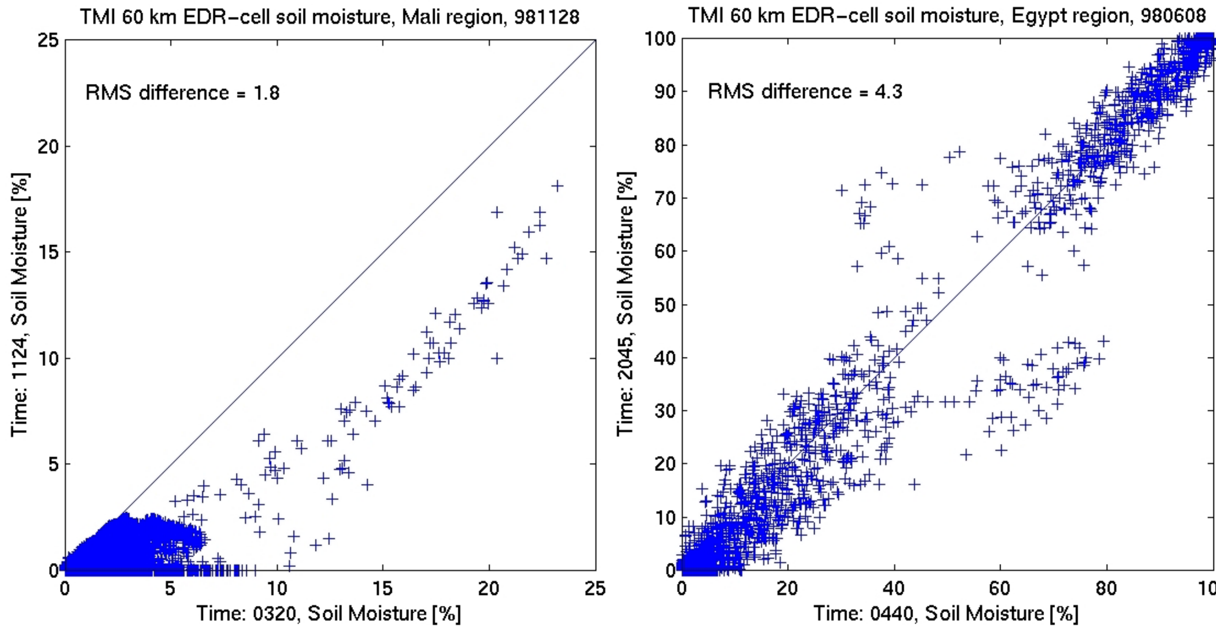
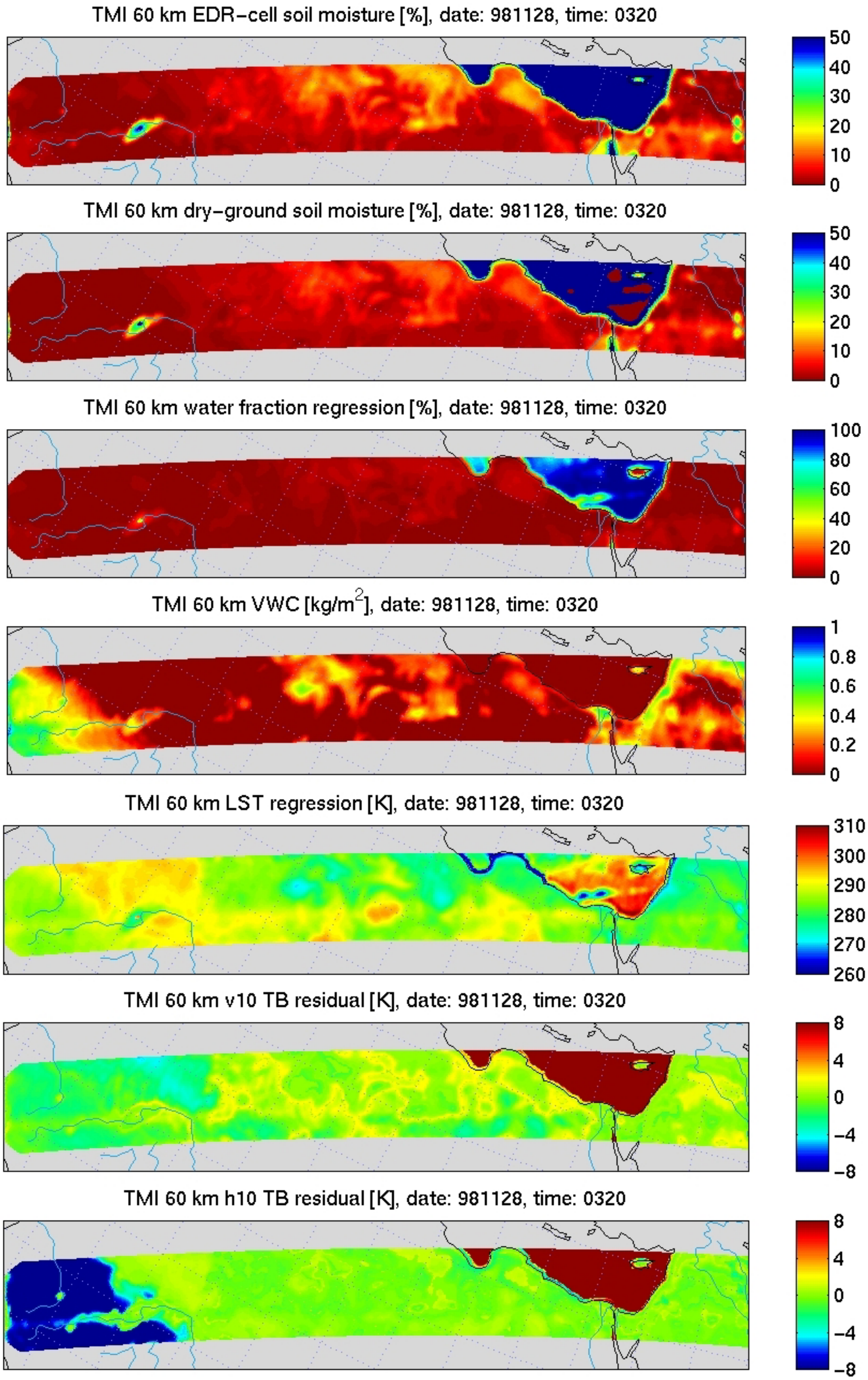


Figure 5-3 maps many of the algorithm retrieval and diagnostic products for the Mali a.m. swath. Juxtaposition of the water fraction regression and dry-ground soil moisture retrieval with the EDR-cell soil moisture product shows how these intermediate products contribute to the EDR. Note that according to equation (10), the contribution of dry-ground soil moisture to the EDR decreases with retrieved water fraction. Consequently, over open ocean the EDR is effectively equal to the water fraction regression although the algorithm attempts to retrieve dry-ground soil moisture there. The wetlands on the Niger River (first quarter of swath) are an area where retrieved water fraction is moderate and the algorithm retrieves higher than average dry-ground soil moisture. Both products may be sensing a mixture of open water (perhaps shielded by some vegetation) and elevated soil moisture. Water fraction retrieval errors are apparent in the open desert where we assume no open water is present (middle of swath). Here, the physical algorithm retrieves elevated dry-ground soil moisture and VWC. Although higher soil moisture and vegetation may be present, the algorithm is more likely compensating for other effects such as surface roughness or topography that the retrieval model does not match accurately in these regions.

Figure 5-3: Mail a.m. swath retrieval products and diagnostics



Using this data set, surface roughness parameters Q and h have been crudely tuned to better match local conditions and any TMI TB biases. The adjusted parameters—arrived at by halfing the baseline parameters—and the baseline set are given in Table 4-3. As see in Table 5-9, variability in roughness parameters is a major source of bare-soil retrieval error in simulations; any deviations in the model's roughness parameterization from true roughness conditions can be expected to increase soil moisture retrieval error. Consequently, if one roughness parameter set is to be used globally, it is important that the parameters be tuned to accurately represent global roughness conditions—and any TB measurement biases—in order to minimize biases in the EDR. At this stage—that is, without ground truth—we use TB convergence as a surrogate metric for retrieval quality. In later phases, studies where ground truth is available will help to validate both the relationships in the physical model between model parameters, inputs, and retrieved quantities as well as the soil moisture product itself. It is important in general that the algorithm converges while retrieving soil moisture accurately in validation tests: Good physical model validation helps improve retrieval performance confidence for the full range of conditions not tested by ground truth.

Whereas Figure 5-3 shows retrievals with the lower-adjusted roughness parameters, Figure 5-4 shows TB residuals (retrieval forward model TB minus TMI-measured TB) for the retrieval algorithm using baseline roughness parameters. Some regions converge (zero TB residual) with both parameter sets but overall convergence is significantly improved using the lower roughness parameters. Baseline convergence errors are especially large where no vegetation cover is retrieved (or expected) and the impact of incorrect roughness assumptions is highest. Neither case converges well for H-pol. where there is known dense vegetation (far left of swath). This is a consequence of retrieval model limits on VWC to the applicable range of the model's parameterization. Use of TB residuals in real-time quality control retrieval evaluation is an advantage of the physical retrieval approach.

Figure 5-4: Mali a.m. swath TB residuals with baseline roughness parameters

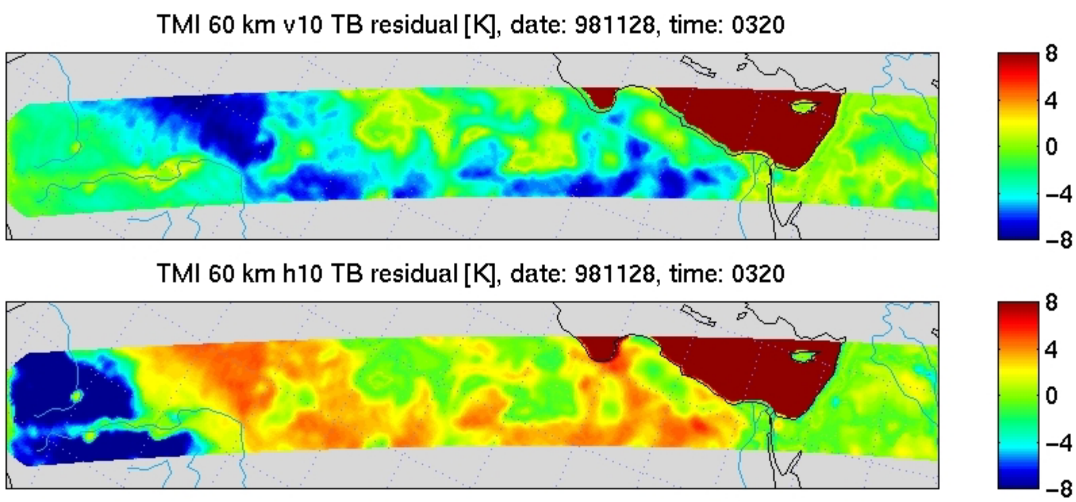
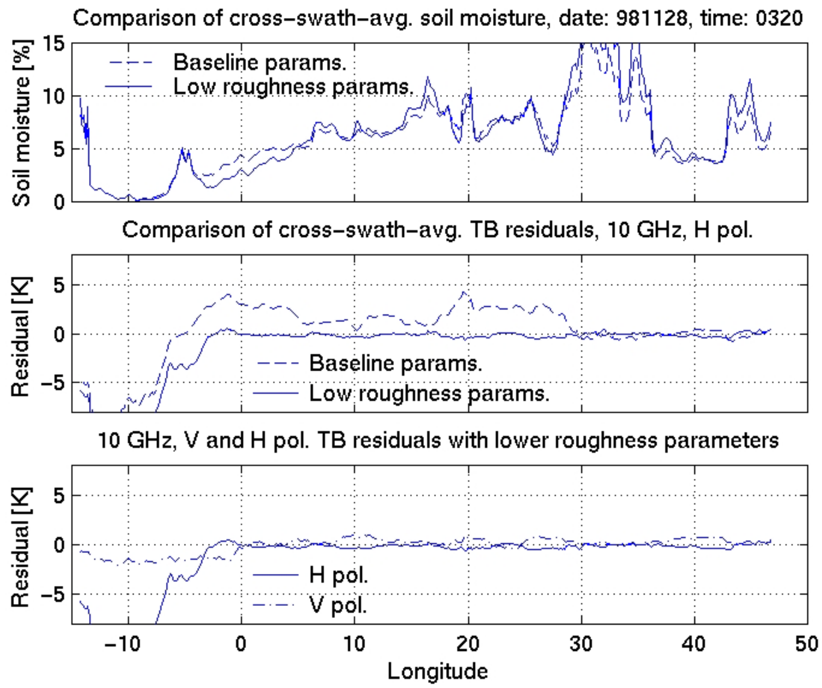


Figure 5-5 compares retrieval results using the baseline and lower roughness parameter sets. The plots show cross-swath averages of retrieved soil moisture and brightness temperature residuals (retrieval model minus measurements) plotted against swath longitude (as mapped in Figure 5-3 and Figure 5-4). Ocean retrievals are not included. The lower roughness settings reduce retrieved soil moisture where no vegetation is retrieved (e.g., around 0 longitude) and reduce or eliminate brightness temperature residuals. Further residual reduction may be achieved—for example, by modifying the VWC threshold that controls whether bare soil background statistics are enforced—but are not justified as long as larger error sources (primarily vegetation retrieval) are present.

Figure 5-5: Swath-average comparisons with different roughness parameter sets



Referring back to Figure 5-2, RMS day-night difference errors were up to 30% lower when the higher baseline roughness parameters were used. However this is not a good metric for roughness parameter evaluation. Higher roughness parameters have two effects on retrieval model brightness temperatures: (a) Q-parameter polarization mixing reduces V-pol. while increasing H-pol. and (b) h-parameter roughness brightening increases both polarizations. Consequently, H-pol. is always brightened by roughness while V pol. may be brightened or darkened depending on the relative magnitudes of these two effects. The retrieval algorithm compensates somewhat for roughness brightening with lower VWC retrievals. But if the roughness parameters are set to high or incompatible values, there may be no mechanism for the model to match measured brightness temperatures—that is, the retrieval does not converge. The effect of increased retrieval soil moisture would be to lower both V and H pol. brightnesses. In TMI retrievals with the baseline roughness parameters, the algorithm returns lower soil moisture and V and H pol. residuals are equal but with opposite sign (V negative, H positive). Consequently, the day-night retrieval differences are lower due to a higher incidence of limiting cases (e.g., zero soil moisture retrieval) and cases with retrieved soil moisture less than 25% where errors are lower (see Table 5-4).

5.5.2. SMMR Retrieval Tests

The Nimbus-7 Scanning Multi-channel Microwave Radiometer (SMMR) provides the best available dataset to date for testing the CMIS soil moisture algorithm with simultaneous 6 and 10 GHz data. Relevant SMMR specifications are given in Table 5-16. Global earth-gridded SMMR Pathfinder Brightness Temperatures were acquired from the National Snow and Ice Data Center (NSIDC). As noted by Njoku and Li (1999), uncertainties in SMMR absolute calibration are generally impossible to distinguish from uncertainties in retrieval model parameters (primarily Q, h, and ω). We have adopted their values for Q and h (Table 4-3) derived over two calibration sites and use the SMMR dataset to demonstrate the robustness, consistency, and flexibility of the algorithm with both 6 and 10 GHz data. The algorithm was also modified (a) to simultaneously retrieve LST based on only 6 and 10 GHz data and (b) to retrieve water fraction as a binary water/no water flag (because of the lack of a water fraction regression model for SMMR).

Table 5-16: Nimbus-7 SMMR instrument characteristics

	Scanning Multichannel Microwave Radiometer (SMMR)				
Channels [GHz]	6.6V/H	10.7V/H	18V/H	21V/H	37V/H
Nominal resolution [km]	148x95	91x59	55x41	46x30	27x18
Swath width [km]	780	780	780	780	780
Incidence angle [deg]	50.3	50.3	50.3	50.3	50.3
NEDT [K]	0.7	0.8	0.9	1.0	1.4

Figure 5-6 shows soil moisture and VWC retrieved over North Africa from descending SMMR passes on days 002 and 180, 1985. Notable features include (a) the anomalously high soil moisture and VWC in the 0 longitude swath on day 180, (b) realistic retrieval of the north-south vegetation gradient around 10N, and (c) dry deserts and sharp coastlines. It is unclear what is causing elevated soil moisture and VWC in one swath. Simultaneous LST retrieval errors are likely to be significantly higher than TMI LST regression errors and could cause regional soil moisture retrieval bias.

Figure 5-6: SMMR soil moisture and VWC retrieval maps, days 002 and 180, 1985

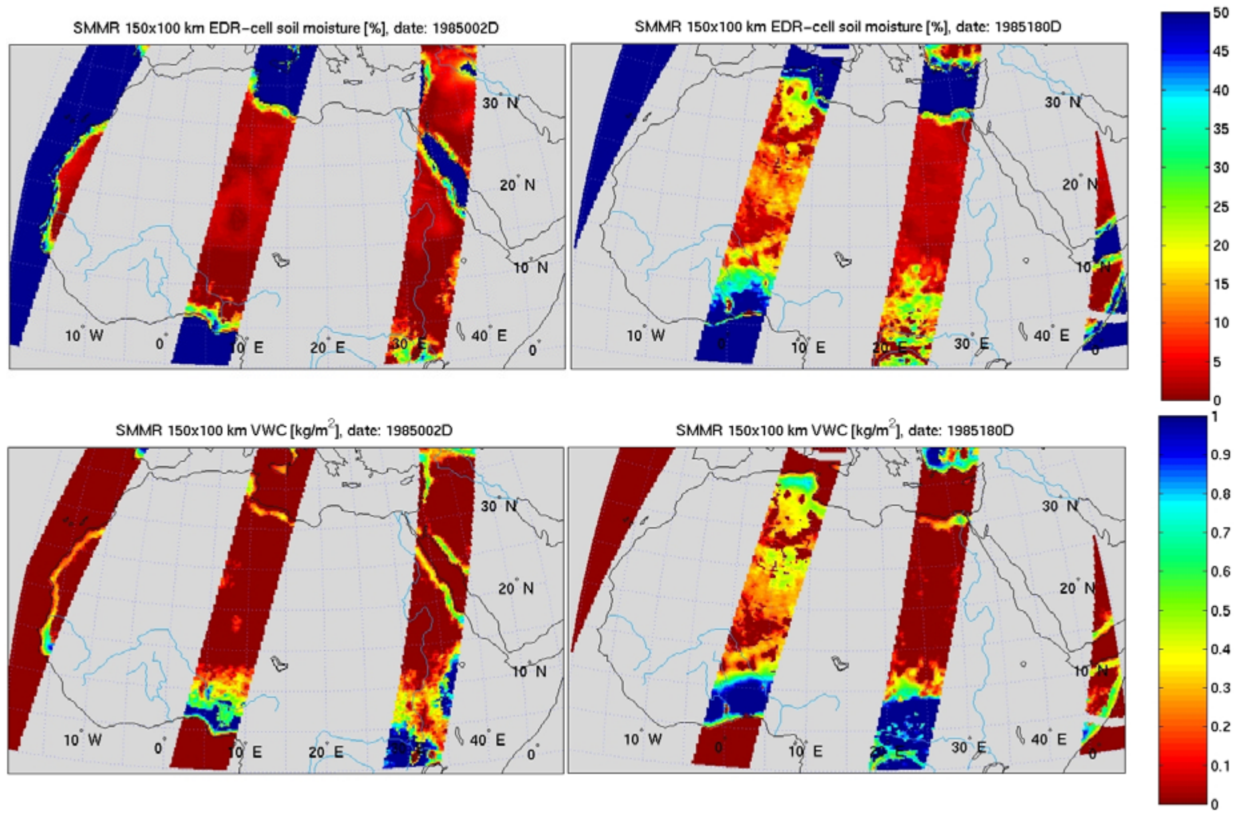
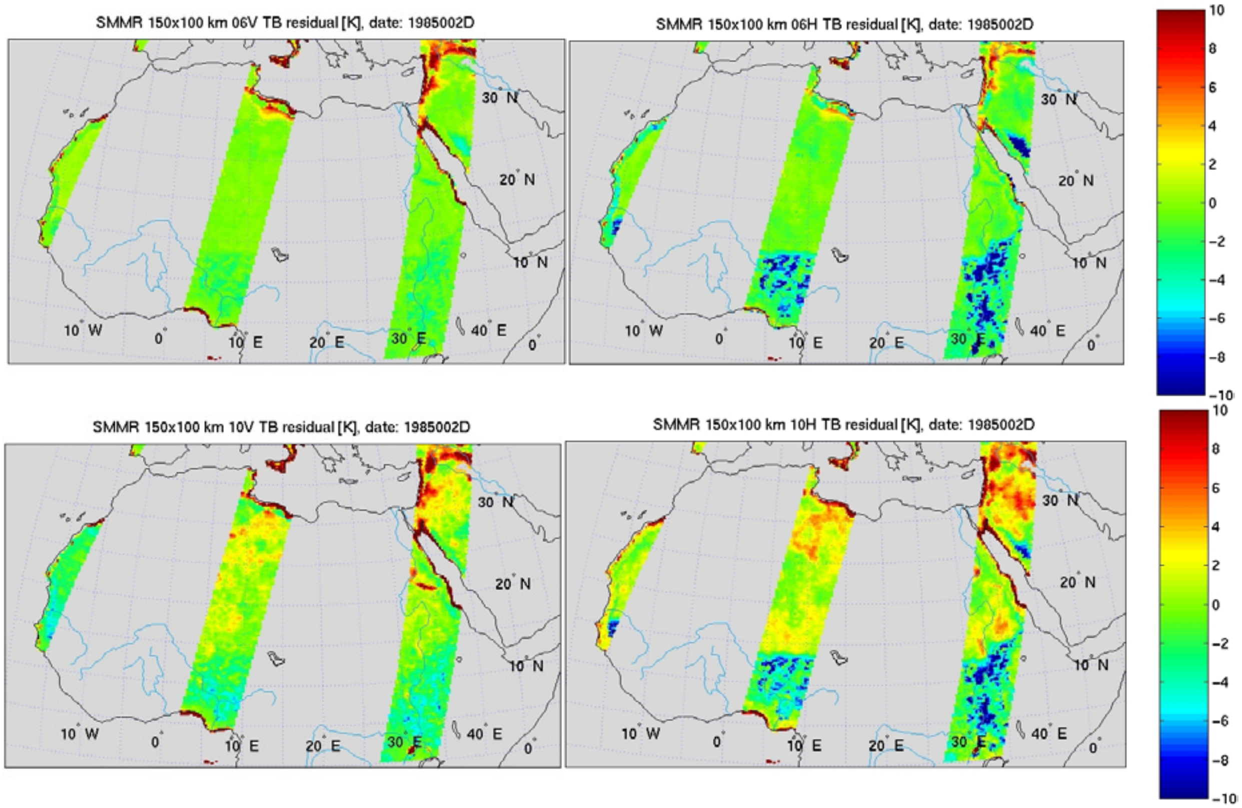


Figure 5-7 shows retrieval model TB residuals (retrieval forward model TB minus SMMR-measured TB) for the day 002 scene. As with TMI, residuals are generally low indicating good retrieval model convergence except where dense vegetation is expected.

Figure 5-7: SMMR TB residual maps, day 002, 1985



6. Algorithm Calibration and Validation Requirements

6.1. Pre-launch

To be completed.

6.2. Post-launch

To be completed.

6.3. Special considerations for Cal/Val

To be completed.

6.3.1. Measurement hardware

To be completed.

6.3.2. Field measurements or sensors

To be completed.

6.3.3. Sources of truth data

To be completed.

7. Practical Considerations

7.1. Numerical Computation Considerations

All soil moisture algorithm modules must execute after (a) derivation of 40 km emissivity and surface temperature by the atmospheric Core Module and remapping of those products to the earth grid and (b) derivation of current surface type conditions by a module of the Vegetation/Surface Type algorithm. Implicit in this arrangement is that the 50 km Core Module products are produced prior to its 40 km products. The 50 km module of the soil moisture algorithm may execute before the 40 km Core Module products are remapped to the earth grid.

7.2. Programming/Procedure Considerations
To be completed.

7.3. Computer hardware or software requirements
To be completed.

7.4. Quality Control and Diagnostics
To be completed.

7.5. Exception and Error Handling
To be completed.

7.6. Special database considerations
To be completed.

7.7. Special operator training requirements
To be completed.

7.8. Archival requirements
To be completed.

8. Glossary of Acronyms

AMSR	Advanced Microwave Scanning Radiometer
ATBD	Algorithm Theoretical Basis Document
AVHRR	Advanced Very High Resolution Radiometer
BT	Brightness Temperature [K]
CMIS	Conical Microwave Imaging Sounder
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellite Program
EDR	Environmental Data Record
EIA	Earth Incidence Angle
FOV	Field Of View
IFOV	Instantaneous Field Of View
LST	Land Surface Temperature [K]
NPOESS	National Polar-orbiting Operational Environmental satellite System
RFI	Radio-Frequency Interference
RMS	Root Mean Square
RMSE	Root Mean Square Error
SDR	Sensor Data Record
SSM/I	Special Sensor Microwave/Imager
SSMIS	Special Sensor Microwave Imager Sounder
TB	Brightness Temperature
TMI	TRMM Microwave Imager
TOA	Top-of-Atmosphere (i.e., measured by sensor)
TRMM	Tropical Rainfall Measuring Mission
USGS	United States Geological Survey
VIIRS	Visible/Infrared Imager/Radiometer Suite

VIRS	Visible and Infrared Radiometer System (on TRMM)
VST	Vegetation/Surface Type
VWC	Vegetation Water Content [kg/m2]

9. References

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